

# OWNERSHIP AND HEALTH CARE

A Dissertation

by

JEREMY NIGHOHOSSIAN

Submitted to the Office of Graduate Studies of  
Texas A&M University  
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Li Gan
Committee Members,	Timothy Gronberg
	Stephanie Houghton
	Joanna Lahey
	Thomas Saving
Department Head,	Timothy Gronberg

May 2013

Major Subject: Economics

Copyright 2013 Jeremy Nighohossian

## ABSTRACT

The United States Health Care sector is a large and growing segment of the US economy. Herein, I present three distinct research projects regarding aspects of that industry, especially how it responds to public policy and government programs. I focus primarily on the hospital sector, and the Medicare Advantage market. Additionally, I explore how ownership type—publicly owned versus for-profits, for example—behave differently.

I investigate the relative efficiency of different ownership types in the US hospital industry. Earlier studies neglect the differential ability of the hospital types to choose their own market. We use a Dubin-McFadden approach to solve the endogeneity problem and estimate hospital efficiencies for each ownership type. Efficiencies are estimated using stochastic frontier analysis. Results indicate that accounting for location choice does affect estimates of efficiency and that for-profit hospitals have a relative advantage in smaller markets while public hospitals have a slight edge in larger markets.

Next, I study entry decisions of insurance plans participating in the Medicare Advantage program. I use the prevailing models of entry to compare how for profit and non-profit insurance firms differentially emphasize the characteristics of potential markets. I also determine how the preferential treatment of non-profits affects the composition of markets and whether governments should adjust their treatment to encourage or discourage non-profit entry. Results indicate that non-profit insurance companies are more responsive to higher payment rates which suggests that they act more like for-profit firms than altruistic organizations.

Finally, I estimate the how much net welfare, Medicare Advantage contributes

to the US economy. I use the Medicare Current Beneficiary Survey to estimate a discrete choice model of beneficiaries' choice of traditional Medicare, Medigap, and Medicare Advantage. I use the results to calculate the net welfare; I find that Medicare Advantages, on net, increased social welfare by 7.76 billion dollars in 2005.

## ACKNOWLEDGEMENTS

Of course, a project of this magnitude cannot be accomplished without the help and support of many people. First, I would like to acknowledge the contributions of my committee, Li Gan, Tim Gronberg, Stephanie Houghton, Joanna Lahey, and Tom Saving. They all provided terrific and actionable feedback and helped me improve as an economist. Special thanks to Li Gan and Stephanie Houghton as they made numerous suggestions and offered great advice to aid in both my graduate career and my future professional career.

Secondly, I would like to thank the Private Enterprise Research Center and its staff for employing me and providing me the resources to help me make my own contributions to the field. Andy Rettenmaier has been an especially valuable asset in molding my own research.

Next, thanks to the Economics Department and its faculty and staff. The former taught me more than I ever thought I would know about the discipline (and hopefully enough so that they are not ashamed to claim me in the future). The staff, of course, made sure I was always pointed in the right direction and the myriad forms, applications, requests were filled out and submitted properly.

Lastly, I must thank my family and friends for all of their (not necessarily academic) support. Obtaining a Ph.D. is a herculean effort with ups and downs. Some provided financial support and some emotional, but both were necessary. My work would not be the same without them.

## NOMENCLATURE

CMS	Centers for Medicare and Medicaid Services
MA	Medicare Advantage
ARF	Area Resource File
HHS	Health and Human Services
HRSA	Health Resources and Services Administration
MCBS	Medicare Current Beneficiary Survey
OOP	Out of Pocket
AARP	American Association of Retired Persons

# TABLE OF CONTENTS

	Page
ABSTRACT . . . . .	ii
ACKNOWLEDGEMENTS . . . . .	iv
NOMENCLATURE . . . . .	v
TABLE OF CONTENTS . . . . .	vi
1. INTRODUCTION TO RESEARCH . . . . .	1
2. SELECTING INTO EFFICIENCY IN THE US HOSPITAL MARKET . .	2
2.1 Introduction . . . . .	2
2.2 Literature . . . . .	5
2.3 The Model . . . . .	9
2.3.1 Cost Function . . . . .	9
2.3.2 Inefficiency Term . . . . .	12
2.3.3 Location Choice . . . . .	13
2.4 Data . . . . .	16
2.5 Results . . . . .	20
2.5.1 Dubin-McFadden . . . . .	20
2.5.2 Frontier Analysis . . . . .	21
2.6 Conclusion . . . . .	27
2.6.1 Discussion . . . . .	27
3. INCENTIVIZING OWNERSHIP: CAN GOVERNMENT AFFECT FIRM COMPOSITION . . . . .	29
3.1 Introduction . . . . .	29
3.2 Literature . . . . .	31
3.3 Industry Background . . . . .	34
3.4 Data . . . . .	35
3.4.1 Firm Definition . . . . .	37
3.4.2 Potential Entrants . . . . .	39
3.4.3 Payments . . . . .	40
3.4.4 Moments . . . . .	41
3.5 The Model . . . . .	41
3.6 Estimation Procedure . . . . .	42
3.7 Results . . . . .	43

3.8	Conclusion . . . . .	45
4.	THE WELFARE EFFECT OF MEDICARE ADVANTAGE: A MICRO APPROACH . . . . .	47
4.1	Introduction . . . . .	47
4.2	Literature . . . . .	49
4.3	The Model . . . . .	50
4.3.1	Insurance Plan Choice . . . . .	50
4.3.2	Program Choice . . . . .	51
4.3.3	Implementation . . . . .	52
4.3.4	Consumer Surplus . . . . .	53
4.3.5	Net Costs of Medicare Advantage . . . . .	53
4.4	Data . . . . .	54
4.4.1	Overview . . . . .	54
4.4.2	Medigap . . . . .	55
4.4.3	Medicare Advantage . . . . .	56
4.5	Results . . . . .	58
4.5.1	Net Costs of Medicare Advantage . . . . .	59
4.6	Conclusion . . . . .	60
4.6.1	Discussion . . . . .	60
5.	DISSERTATION CONCLUSION . . . . .	62
	REFERENCES . . . . .	63
	APPENDIX A. TABLES . . . . .	68
	APPENDIX B. FIGURES . . . . .	80

## 1. INTRODUCTION TO RESEARCH

The United States Health Care sector comprises the interactions of consumers, firms, and the government in several capacities. Firms in different industries work as both consumers and providers and can be organized to earn profits or to altruistically provide services to those who need them. The government, too, plays different roles at different times. The Federal government acts as an insurer with Medicare but also subsidizes health care for low-income Americans through Medicaid. Local governments sometimes set up hospitals when their citizens are under-served.

With all of these relationships co-existing in different industries creating such a multifarious system that at its core is meant to merely provide a service to citizens, opportunities to explore the benefits and costs of different aspects abound. In my dissertation, each section concentrates on a separate industry within the health care sector: hospitals, insurance, and Medicare Advantage. In the first two sections, I explore the differences between different ownership types, and in the third I explore the benefits of the Medicare Advantage program—a program meant to orient private firms to public goals.



## 2. SELECTING INTO EFFICIENCY IN THE US HOSPITAL MARKET

### 2.1 Introduction

Economists have long studied how the performance of publicly-owned firms compares to that of conventional firms—private firms run for profit. Though in most settings, for-profit firms are best able to provide goods and services in a way that enhances social welfare, in certain circumstances, particular features might dampen their advantages. In this paper, we investigate the relative performance of three types of firms—public, non-profit, and for-profit—in the hospital industry. We find that the market in which the firm operates is an integral factor in the analysis, and that though for-profit firms outperform their counterparts in the smallest markets, public firms perform just as well as private in the largest.

Public firms seem to have several potential advantages over their counterparts: lower tax rates, favorable legislation, and altruistic employees to name a few. The advantages of the for-profit firms, derived from the self-interested motives of owners, seem to outweigh those of government-managed firms in most industries. The First Fundamental Welfare Theorem predicts that private, for-profit firms will lead to maximum social welfare, but if certain conditions aren't met—perfect competition, absence of externalities, absence of information asymmetry to name a few—welfare may not be maximized.

The hospital industry fails two of the requirements for the First Fundamental Welfare Theorem—asymmetric information and (in many markets) lack of competition. Past research on which ownership type outperforms the other has had mixed results; unsurprisingly, the answer depends significantly on the specifics of the question— which industry, which setting, which measure of performance?

Additionally, even within a single industry, there may not be a single answer; one ownership type might perform better only in certain circumstances. For example, different competitive environments might have different effects on the efficiency of firms depending on their ownership type. Furthermore, the incentives that go along with each ownership type may also complicate the measurement of their performance.

We explore these issues within the hospital industry. Hospitals foster a great deal of analysis because the industry operates in a diverse set of environments—hospitals exist in both rural and urban areas, in monopolies and competitive markets, and with large and small capacities. Additionally, they are organized under three different ownership types.

The health care industry makes up a significant proportion (16%) of the US economy, and it is expected to continue growing in the future. Hospitals are the primary conduit through which consumers participate in the health care industry. Though the size of the industry makes it important, one aspect that makes it unique is its inclusion of different ownership types. In this paper we explore which ownership type operates most efficiently. Though many have previously studied this issue, we will address the complicating effects that hospitals' incentives (and how they're manifested in location choice) will have on the estimates.

The hospital industry is the only industry characterized by considerable competition between firms that are operated by government (at multiple levels), not-for-profit organizations, and for-profit enterprises. This aberration developed because early hospitals focused on the indigent. Serving this population proved not very profitable and, therefore, was eschewed by for-profit firms and, therefore, dominated by public and non-profit hospitals. As the industry matured and evolved, however, hospitals expanded to serve a larger segment of the population, but non-profit and public hospitals continued to dominate Starr (1982). Many argued that information

asymmetries explained their persistence, but perhaps the for-profit hospitals needed more time to react. Indeed, over the past few decades, for-profit hospitals have become a significant participant in the hospital industry.

Of course, for-profit hospitals likely have different incentives than public and non-profit hospitals and, therefore, will behave differently. Many examples of different behaviors are discussed below. We will focus on how these hospitals have different incentives and constraints when choosing where to locate and how their motivations may bias our evaluation of their performance.

The measure of performance that this paper focuses on will be technical efficiency, or how well the hospital can minimize its cost. We will use Stochastic Frontier Analysis (SFA) on data from a national sample of hospitals to determine each hospital's distance from the cost frontier. Also, we will estimate the model in a two-step discrete/continuous method to address the bias caused by the ability of for-profit hospitals to choose the markets they serve. We employ the hospital cost reports provided by the Centers for Medicare and Medicaid Services (CMS).

We find that in the uncorrected data, for-profit hospitals are more efficient than public, and public are more efficient than non-profits in all markets. Once we control for their location choices, however, we find that for-profit hospitals continue to perform better than the other types in smaller markets, but public hospitals and for-profit hospital efficiency are not significantly different in the largest markets. Additionally, non-profits and public hospitals operate at similar levels of efficiency in medium-sized markets.

In other words, the ability and inclination of firms to choose in which market they operate biases our measurements of their performance, and different ownership types' ability to provide services at the lowest cost depends on the market in which they operate. Though an analysis that controls for only ownership type may result

in a single ordering, this obscures the more complicated truth that each has its advantages in different settings and it fails to consider that firms' location choice might bias measurements of their performance.

## 2.2 Literature

Economists have long been interested in the motivations of for-profit firms and wondered if they are consistent with social welfare maximization. Could publicly owned enterprises better promote social welfare if the incentives were aligned? Do non-profits offer a combination of the other two types' best aspects? The health industry offers a fertile battleground to test these ideas.

Alchian (1965) proposed the earliest and most influential theory regarding ownership and efficiency. Basically, he argued that because the owners of a public firm (citizens) couldn't easily transfer their ownership claims, specialized owners would be unable to gain control of the firm and manage it efficiently. Scores of studies in the ensuing years in several industries attempted to test this notion without reaching a consensus. Caves and Christensen (1980) argued that the competitive environment could compel public firms to operate as efficiently as private, and again subsequent economists found evidence for and against their hypothesis.

For hospitals in particular, several papers have proposed models for how non-profit hospitals operate—what incentives they face and their objectives. For example, Newhouse (1970) suggested that each of the parties involved in the operation of a non-profit hospital have different motivations and participate in a constant struggle to direct the hospital. The government that bestows upon it special privileges desires it to serve as many citizens as possible—quantity maximization. On the other hand, the Board that oversees the hospital may solicit donations to the hospital by advertising its “prestige,” which may be tied to both the quantity produced and the quality

of the product. The medical staff, also, has its own interest in both quantity and quality. Consequently, the final objective of the non-profit hospital is a compromise between the different stakeholders.

In his model, the non-profit firms do *not* minimize costs because the incentives will push non-profits to over-emphasize *quality* (compared to a for-profit hospital). Therefore, the presence of public or non-profit firms will drive the equilibrium away from the social optimum. The high barriers to hospital entry also prevent entry pressure from disciplining the non-profits and public hospitals as in other industries.

Pauly and Redisch (1973) proposed an alternative model for non-profit hospitals. They posited that the medical staff, namely the doctors, had unfettered control of the hospital and that they acted to maximize their own net incomes, i.e. a physicians' cooperative. This arrangement would mimic a for-profit enterprise because the physicians would have the incentive to maximize the economic residual as it would accrue to them. This case leads to similar outcomes as in the Newhouse model—overemphasis on quality and duplication of several services. Ultimately, however, it relies on the assumption that the physicians are the only decision-makers involved in supply.

Once the models were in place, economists began to compare the performance of the hospital types to ascertain which model better fit the outcomes. Over time, the methods have evolved to be more sophisticated, moving from direct comparisons of raw outcomes to regression analysis to frontier methods. At no stage did they find consistent behavior in terms of cost efficiency across ownership types. Sloan (2000) discusses the most prominent papers during the pre-frontier era.

The regression analysis gave way to frontier approaches in the early 1980s. In the frontier approach, a production (or cost) frontier is estimated to determine the most cost-effective way to provide a certain amount of output. Then the hospital's

distance from the frontier determines its efficiency. The two primary frontier-based methods, Data Envelopment Analysis and Stochastic Frontier Analysis, have both been used in numerous studies. In the past decade, SFA has become more dominant in the hospital efficiency literature.

The first two to apply it to hospitals, Stephen Zuckerman (1994) and Vitaliano and Toren (1996), find mixed results. The former finds that while public and non-profit hospitals have similar efficiencies, they both outperform for-profits. The latter finds that all three ownership types are equally adept (or inept) at minimizing costs. Also, while Stephen Zuckerman (1994) was primarily interested in ownership's effect on performance, Vitaliano and Toren (1996) focused on other variables but included ownership as a control. Both of these papers used a two-step method wherein the frontier is estimated in the first step, and the inefficiencies are regressed on other determinants in a second step; later researchers pointed out that this procedure is biased, however. Like Vitaliano and Toren (1996), many other researchers include ownership type in their analyses though it's not their primary interest. The results of these studies suggest no clear relationship between ownership type and efficiency.

When comparing the performance of three different ownership types, there are thirteen possible orderings (six distinct orderings, six orderings where two of the three types are statistically the same, and one where all three types are statistically the same). Of the seventeen analyses conducted in the listed papers, twelve compared all three types, and seven different orderings were reported. The remaining five analyses compared only non-profit hospitals and for-profit hospitals. With only two ownership types, there are only three possible orderings; all three possibilities were reported in at least one study.

Some studies Carey (2003), Chirikos and Sear (2000), McKay and Deily (2005), Folland and Hofer (2001), Li and Rosenman (2001), McKay and Dorner (2002),

Rosko (1999), Sloan (2000), and Stephen Zuckerman (1994) look at a national sample of all hospitals, while others focus on certain geographic areas or types of hospitals: Rosko and Mutter (2010) look at Critical Access Hospitals; Ozcan and Haksever (1992) look at urban hospitals; Vitaliano and Toren (1996) concentrate on hospitals in New York state. These papers also differ in their methodology, some use DEA and some use SFA with the two-step procedure to determine the contributors to inefficiency.

What none of these analyses consider, however, is the varying amounts of control over seemingly exogenous sources of variation these ownership types have. For example, if hospitals exhibit positive returns to scale, then hospitals with more admissions will appear more efficient than low-admission hospitals. This wouldn't be a problem if the different types of hospitals were equally likely to locate in areas across the admissions spectrum. However, for-profit and public hospitals, in particular, have vastly different entry philosophies: for-profit hospitals can choose areas that have high expected profits, while public hospitals are generally established in areas that lack hospital service. This is borne out in the data, where we see that public hospitals tend to serve smaller communities and for-profits larger communities. Non-profits could be expected to behave either like for-profits or like public hospitals depending on the objectives of its donors and/or managers. Regardless, this complication makes the location endogenous.

To address this endogeneity, we use the approach developed in Dubin and McFadden (1984), wherein the first step is a discrete choice model and the second step uses the predicted results from the first step as instrumental variables. Though applied to electricity consumption in the original paper, since then, it has been extended to answer diverse questions; fuel economy, (Goldberg (1998) and Feng, Fullerton and Gan (2005)), finance (Fohlin (1998)), and labor (Seitz (2009)) to name just a few

examples.

Several economists have applied this methodology to the health care sector. Most commonly it is used in the context of how the quantity of health services purchased relates to the choice of insurance provider—for example, Cameron et al. (1988), Cardon and Hendel (2001), and Mello, Stearns and Norton (2002). While Cardon and Hendel (2001) focused primarily on the role of adverse selection, Cameron et al. (1988) also looked at moral hazard. Mello, Stearns and Norton (2002) were interested in determining to what extent HMOs reduce the resource demands of their insurees.

The objective of this paper is to determine how the choice of location influences the efficiency estimates of the different ownership types. We will use a discrete choice model to estimate the likelihood that hospitals will locate in different market types, and then use the probabilities as IVs in a stochastic frontier framework. By doing this we will neutralize the bias caused by the endogeneity of location choice.

## 2.3 The Model

### 2.3.1 Cost Function

Stochastic Frontier Analysis has been used to study hospitals for decades. As such, there are innumerable variations of the models used. At its most basic level SFA estimates a cost function for the hospital industry and infers the inefficiency of the hospital from the residual. Rosko and Mutter (2008) provide a survey of the methods and techniques of some of the analyses to identify common/best practices. The basic equation that we will estimate is

$$\ln costs_i = C(Y_i, W_i, X_i) + v_i + u_i \quad (2.1)$$

where  $Y_i$  denotes outputs,  $W_i$  denotes input prices, and  $X_i$  denotes quality descrip-



tors.  $v_i$  represents the stochastic component of the costs while  $u_i$  represents a the distance from the cost frontier for that hospital.

For  $C(Y_i, W_i, X_i)$ , we use a log-quadratic translog cost function,

$$\begin{aligned}
C(Y_i, W_i, X_i) = & \sum_{\text{outputs}} \alpha_m \ln y_{mi} + \sum_{\text{prices}} \beta_n \ln w_{ni} + \sum_{\text{outputs}} \sum_{\text{prices}} \gamma_{mn} \ln y_{mi} \ln w_{ni} \\
& + 0.5 \sum_{\text{outputs}} \sum_{\text{outputs}} \alpha_{mj} \ln y_{mi} \ln y_{ji} + 0.5 \sum_{\text{prices}} \sum_{\text{prices}} \beta_{nk} \ln w_{ni} \ln w_{ki} + \sum_{\text{descriptors}} \delta_r x_{ri} + \beta_0
\end{aligned} \tag{2.2}$$

Rosko and Mutter (2008) find that both the translog and the Cobb-Douglas specifications generally lead to the same results.<sup>1</sup> we use the translog because of its flexibility, its primacy, and its ability to include multiple outputs. Also, many choose Cobb-Douglas when they have few degrees of freedom to spare, but generally that is not a problem when using a national sample of hospitals. Finally, studies have found that though the choice of cost function may affect *absolute* measures of inefficiency, it doesn't affect the *relative* inefficiencies of the firms. Because we are most interested in the relative measures of inefficiency, the choice's repercussions will be limited.

For outputs, we use outpatient visits and total admissions. We excluded patient days because of the high correlation with admissions. While previous literature frequently includes more outputs, we feel that outpatient visits and admissions are the primary descriptors of hospital output and additional variables will only provide marginally more information. As no consensus has emerged regarding the use of other variables, and there are no clear arguments in favor of any other particular variables, the inclusion of other variables is not required.

The input prices include both the labor price (wages plus benefits divided by

---

<sup>1</sup>This may not be the case when the residuals are regressed on causes of inefficiency. See Battese and Broca (1997).

full-time employees) and the price of capital (the sum of depreciation and interest expense divided by the number of beds). These two prices are included in nearly every analysis of hospital performance and are the only indicators of price included, owing largely to the scarcity of alternatives. To ensure homogeneity of degree one in input prices, the cost function is normalized by the price of labor.

Because hospitals' efficiency could be largely influenced by the severity of the patients it sees and the quality of the hospital itself, it becomes important to control for these dimensions. For quality, the most commonly included variables are hospital accreditation status, risk-adjusted mortality rate, and teaching status. Due to data limitations we include only teaching status. While we have the option of providing a continuous measure (such as interns per bed), this has the unwelcome side effect of being endogenous. The alternative, a teaching dummy is not without downsides either; it suggests that hospitals that train doctors are inherently of a different quality than non-teaching hospitals.

Hospital systems exist ostensibly to help reduce the costs of operating hospitals by relying on economies of scale. Hospitals joining or creating systems almost uniformly motivate their decision by appealing to the cost reduction potential of the integration, though Carey (2003) notes that the evidence supporting this supposition is mixed at best. Regardless, it is important to include it as a contributor to the cost function because it's a structural parameter that will likely have a significant impact on how the hospital is managed.

It is also necessary to account for the mixture of patients that seek treatment. Almost all analyses use the Medicare Case Mix Index (CMI) to account for diversity of cases seen. This has been found to explain away a significant portion of estimated inefficiency. Additional product descriptors only marginally improve the estimated efficiency, and indices of severity have been found to be highly correlated with the

case mix index so need not be included either.

To our knowledge, no previous study has included variables describing the market size, let alone interactions between market size and ownership type. We expect that increased market size should have a negative effect on inefficiency for all ownership types.

### 2.3.2 *Inefficiency Term*

Finally, we must choose a distribution for the error terms.  $v_i$  accounts for shocks to costs outside the control of management and will be standard normal as per common practice.  $u_i$  represents the deviation from the cost frontier and is assumed to be positive. Generally, analysts choose either a truncated normal or a truncated exponential distribution. Rosko and Mutter (2008) found that choice of error distribution had little effect on results. We chose to use the truncated normal distribution as it allows for external variables to affect the efficiency directly. This is done by allowing the parameters of the normal distribution to be determined by these variables.

Using this procedure is an alternative to the two-step procedure discussed previously. Because the elements that affect the efficiency  $z_i$  are likely correlated with elements in the cost function  $x_i$ , estimation of both  $z_i$  and  $x_i$  must take place simultaneously. Estimating in two stages (where the cost function is estimated first and the resulting efficiencies are regressed on  $z_i$ ) will bias the first stage estimates and consequently obviate any second stage. Furthermore, this particular approach is contradictory; in the first stage, we would assume  $u_i$  to be identically distributed, independent of  $z_i$  but in the second that the efficiency is a function of  $z_i$  Kumbhakar and Lovell (2000).

Coelli (1995) proposed a technique to simultaneously estimate both the cost func-

tion and the efficiency components.

$$u_i = \mathbb{N}^+(Z_i\delta, \sigma_u^2) \quad (2.3)$$

$$Z_i\delta = Z_{1i}\delta_1 + Z_{2i}\delta_2$$

Basically, it uses for  $u_i$  a normal distribution truncated at zero with mean  $Z_i\delta$ . So  $Z_i$  determines the mean of  $u_i$  and the point of truncation of  $u_i$ . In other words, higher values of  $\delta$  shift the distribution to the right, expanding the role of  $u_i$ , the efficiency component. Larger  $u_i$  implies that more of the costs are explained by inefficiency. So larger values of  $\delta$  imply increased inefficiency.

Equation 2.3 estimates the contributions of different variables to the inefficiency.  $z_{1i}$  represents a set of market-specific control variables (hospital HHI, median income, average age, and % white) while  $z_{2i}$  comprises dummies for the ownership and market type. The dependent variable will be the total costs of the hospital.

### 2.3.3 Location Choice

To account for the endogeneity of location choice, the first stage of the estimation will attempt to estimate hospital entry into markets of different size.

$$Prob(Y_i = j) = \frac{e^{\beta_j x_i}}{\sum_{k=1}^3 e^{\beta_k x_i}}, \quad j = 1, 2, 3, \dots, J \quad (2.4)$$

Equation 2.4 describes the model being estimated.  $x_i$  represents a set of dummy variables indicating whether the hospital is classified as a certain type (referral, transplant, teaching, critical access, all-inclusive payment system, rehabilitation, sole community, psychiatric, new). The dependent variable in this model,  $Y_i$ , will be  $hospital_i$ 's market type. Market type is determined by the population density of the market, where a higher value of  $j$  denotes higher population density. Specifically, all markets containing at least one hospital are split into  $J$  equally-sized groups. The

lowest population density market is denoted  $j = 1$ , and the market with the highest population density is denoted  $j = J$ .

An alternative method of splitting up the markets would be to divide the counties into three equal groups. This method implies that hospital creators consider a larger set of counties when deciding. While it's appropriate to include all counties in the decision instead of just counties that already contain hospitals, effectively, it would compress the counties most likely to be chosen into fewer groups while inhospitable counties with very few residents would overwhelm the smallest group.

Instead of the multinomial logit model, an ordered probit might be more appropriate since the choices are ordered by population density. However, the model used depends on whether one believes that the hospital has an ideal choice of population density and then chooses the market that contains that choice or if they are actually choosing among market types—rural, urban, a mix. We chose to model the latter option. While others might prefer using the ordered probit, one of the advantages of the Dubin-McFadden framework is that this choice shouldn't affect the qualitative outcome because basically the discrete choice portion creates an instrumental variable, and as long as it's a valid instrument, it will suffice.<sup>2</sup>

To restrict the choice set somewhat, the sample of hospitals is split into six contiguous regions. Theoretically, this suggests that hospital organizers are choosing which type of market they will enter within a particular region. One must assume that the hospital decision is similar across regions for this division to be appropriate. This better approximates the real world since in many cases those who are considering building hospitals generally focus on fairly localized regions instead of the United States as a whole. Using the entire nation for the analysis did not alter the results.

---

<sup>2</sup>In a robustness check, the results were not sensitive to the usage of an ordered probit model in lieu of multinomial logit.

This becomes clearer when one considers the rise of hospital chains. Generally these systems operate on a regional instead of national basis, merging with hospital systems in neighboring states. Rarely do chains undergo cross-country mergers. As such, when determining where to build new hospitals they focus on regions where they already have considerable market information by either filling in a gap in their coverage or expanding to neighboring communities. Cuellar and Gertler (2003) point out that though hospital systems consider geographic risk diversification beneficial, the difficulty with managing separate hospitals in such diverse markets outweighs the benefit.

The data allow for a cursory check of this claim. The hospital can specify whether it is a member of a system and then provide the name and address of that system. Using the data provided, we calculated that the average distance between a hospital and its system headquarters was 34 miles (the median was less than 2). More than 80% of hospitals were located within 50 miles of the system's headquarters. Considering the regions we use span hundreds of miles, there's probably room for even further restricting the choices geographically.

The determined coefficients will be used to predict the probability of each hospital entering each market type. These likelihoods will then be used as instrumental variables for market types in Equation 2.3. If there is selection bias, then the results from the two estimations will differ.

We will divide the results into raw and treated. Raw results come from using market-size dummies directly while treated come from the predicted results of the discrete choice model. The cost functions as well as the efficiency controls ( $z_{1i}$ ) will be the same for both. What will differ will be the variables in  $z_{2i}$ .

$$z_{2i,raw} = \delta_{prof}prof_i + \delta_{pub}pub_i + \sum_j^J \delta_j(popgrp_i = 1) +$$

$$\sum_j^J \delta_{j,prof} prof_i * (popgrp_i = j) + \sum_j^J \delta_{j,pub} pub_i * (popgrp_i = j)$$

$$z_{2i,treated} = \delta_{prof} prof_i + \delta_{pub} pub_i + \sum_j^J \delta_j \widehat{popgrp}_{ji} +$$

$$\sum_j^J \delta_{j,prof} prof_i * \widehat{popgrp}_{ji} + \sum_j^J \delta_{j,pub} pub_i * \widehat{popgrp}_{ji}$$

where  $\widehat{popgrp}_{ji}$  is the predicted likelihood of hospital  $i$  locating in market-type  $j$ .

## 2.4 Data

The hospital data for this analysis come from the Medicare Cost Reports. These reports are submitted by each hospital approved to receive Medicare reimbursements. They are submitted annually to the Centers for Medicare and Medicaid Services (CMS) and contain considerable information about the hospitals; they contain hospital descriptive information such as the name of hospital, location (address), ownership type, and a host of other facility descriptors relating to how the government classifies the hospital. The number of beds is reported as both a total and for each department. The variables that describe the operation of the hospital: admissions, outpatients, labor costs, capital costs, other costs, and net income, for example.

Though both more recent and historic data are currently available, in this paper we use only that from 2009 as it was the most recent finalized set. CMS also provides estimates for the case mix indices for the nation's hospitals on an annual basis. However, the hospitals that submit cost reports to the CMS do not all receive a CMI figure.

Of the hospital records included, CMS did not report CMI's for 2270 of them. Additionally, many hospitals were missing other data from the cost reports. To

address this issue, all missing data were filled in with zeros with the addition of a dummy indicating whether the data were missing. Additionally, since the function was normalized by labor costs, these could not be filled in with zeros. Instead, labor costs were regressed on county health and demographic characteristics. The predicted prices were then used in observations where the actual labor cost was missing. A second dummy variable to indicate the data came from the regression was also added. This way, all available data could be included in the analysis.

Hospital efficiency estimations generally use either MSA or county as their market definition. Neither choice is perfect. Using counties creates a geographic choice area larger than is probable for the decision. Furthermore, it is unlikely that patients are giving equal weight to regardless of distance when considering which hospital to use while ignoring hospitals that may be physically closer yet across a political boundary. Using MSAs still may be too large an area since patients are just as unlikely to cross a large metropolitan area for emergency needs. We choose to use counties as the market definition because of the desire to explore the effect of market size on efficiency. Focusing only on MSAs would limit the scope of the study to only large, urban markets.

The county data come from the Area Resource File. This dataset is provided by the US Department of Health and Human Services Health Resources and Services Administration. It provides medical, geographic, and demographic information for each county in the United States for certain years from 1980-2009. Of the nation's 3143 counties, 2345 of them contain at least one hospital.

Table A.1 provides summary statistics of some of the information used in the analysis split by ownership type. The data above the horizontal line are medians. It is clear from Table A.1 that non-profit hospitals make up the largest segment of hospitals (50%) and controls the largest number of beds (47%). The remaining



hospitals are divided almost evenly between for-profit and public hospitals, but for-profit hospitals have three times as many beds as public hospitals.

Non-profit hospitals have the highest total costs which isn't surprising considering they also serve the most patients. The costs/admission suggest that public hospitals are the least efficient while non-profits are the most. This is in spite of the fact that non-profit and for-profit hospitals have more severe patients to treat according to the CMI.

Generally, for-profit hospitals operate in markets with the most competition and public hospitals in markets with the least. The population density figures correspond to the hospital figures; for-profits operate in the most densely populated areas, public hospitals the least, and non-profits in between. There are 5,380 hospitals in the full sample.

Figures B.1 and B.2 illustrate the main idea of this paper. Figure B.1 shows how the proportions of ownership type evolve as market sizes increase. In the most sparsely populated counties, non-profit and public hospitals overwhelm the hospital markets. As population density increases, however, while non-profit hospitals continue to represent between 40 and 50% of the markets, for-profit hospitals displace public hospitals. This suggests that both for-profit and public hospitals choose their markets differently. We contend that public hospitals operate mostly in smaller communities because public hospitals' intentions are to serve the under-served, and private providers don't find it in their interest to build hospitals there. For-profit hospitals, however, choose denser markets because they expect them to be more profitable than sparse markets.

Table A.2 exhibits the same statistics as Table A.1 but broken down by market type instead of ownership; it makes the relationship between these figures and the size of the markets very clear. All the statistics display a monotonic relationship except

proportion of hospitals, but that division is an artifact of the procedure to divide up the markets. Notice that costs/admission fall with size of market (reinforcing the relationship in Figure B.2 and also, that in the smallest markets, the median hospital faces no competition.

Table A.3 (and Figure B.3) separates the costs/admission by both the market type and ownership type. Figure B.2 shows that costs/patient are lower in denser markets. According to these figures, for-profit hospitals treat patients more cheaply than both non-profit and public hospitals despite the size of the market. However, both public and non-profit hospitals exhibit a marked decrease in costs from the smallest to largest markets—45% for non-profits and 44% for publics. For-profit, on the other hand, falls only 34%. Granted, many factors may be involved here (patient differences for example); this does support the case, though, that competition is a primary factor in the ability of firms to achieve higher operational efficiency.

Figure B.2 shows a similar relationship with aggregating the different ownership types. It, too shows that costs/patient are lower in denser markets, though this could be driven by the varying ownership composition as markets grow.

Figure B.4 shows the locations of the hospitals in the full sample, their ownership type, and the population density of the counties that contain them. The map makes it more clear that hospital density tracks population density. In the lightly populated western counties, most counties have either zero or one public hospital.

## 2.5 Results

### *2.5.1 Dubin-McFadden*

As discussed previously, we divided the counties into groups based on population, each with the same number of hospitals. For the baseline specification we used

three groups.<sup>3</sup> The population density cutoffs for the three types were around 70 people/square mile and 500 people/square mile. Each county type contained about 1790 hospitals in the full sample. As expected from Figure B.1, in the smallest market, non-profits make up 45% of the hospitals, for-profits 15%, and public 40%. In the medium-size markets the composition is 52/32/16, and in the largest markets it is 52/36/12.

The regions used to constrain the entry choices of hospitals can be seen in Figure B.5; they are based on US census regions but modified slightly to maintain similar numbers of hospitals in each region. The coefficients from the multinomial logit can be seen in Table A.4.<sup>4</sup>

They mostly conform to predictions: critical access hospitals are more likely to be in smaller communities while transplant, teaching, rehabilitation, and psychiatric hospitals are more likely in larger markets. New hospitals and hospitals that use an all-inclusive payment system are also more likely to locate in more-populated areas.

Only one coefficient doesn't necessarily match ex ante expectations—referral hospitals. However, hospitals classified as referral hospitals receive patients from neighboring communities that don't have the resources to treat all patients. Medicare classifies hospitals as referral hospitals if they meet 1 of 2 criteria: (1) they surpass a threshold size (in terms of beds) and are located in a rural area or (2) if more than 50% of its Medicare patients are referred from other hospitals and 60% of those referrals are from greater than 25 miles away. This suggests that referral hospitals would probably gravitate to the smaller markets. Large markets probably receive most referrals from other hospitals that are much closer than 25 miles away, and

---

<sup>3</sup>We also performed the analysis dividing counties into four and five groups. Alternate groupings did not significantly affect the qualitative results of the analysis.

<sup>4</sup>These are the results when the national sample is used instead of the regional analysis. These values are not used in the subsequent analysis and are only meant to illustrate the effects.

any referrals from neighboring rural areas would probably be spread out among the many hospitals in an urban area.

There are many ways to assess the performance of this stage. One is to compare the predicted market types to the actual. Figure B.6 maps the predicted market type (when using three market types) to the actual market type. The predicted market type is determined by taking a weighted average of the three groups ( $\sum_{i=1}^J i \cdot \mathbb{P}(j = i)$ ). Though the predictions don't conform exactly to the actual type, the groupings do seem distinct and trend in the correct direction. The predicted market types when compared to the actual market types passed the Kendall correlation test.

Next, one can assess the predicted market type's quality as an instrumental variable. In both of the first stage regressions,<sup>5</sup> the coefficients of the instruments are all non-zero satisfying the rank condition. Additionally, the first stage passes the weak identification test with an F-statistic of 37.650.

### 2.5.2 Frontier Analysis

Table A.5 summarizes the coefficients of the cost function estimation. The left column (raw results) contains the coefficients when the population group dummies are used directly. The right column (treated results) is the estimation using the likelihoods from the multinomial logit. In all cases, the coefficients have the same sign and statistical significance. Additionally, the magnitudes are very similar in almost all cases. There were only 5316 hospitals subjected to the frontier analysis. Fifty-four of the hospitals did not include an ownership type and had to be dropped, while the remainder did not include information used in the multinomial logit stage. Because these hospitals had no predicted county-type, they weren't included in this portion of the analysis.

---

<sup>5</sup>One for each market size other than the reference group which in this case is small markets.

First, notice how the coefficients in the two sets of results are very similar in most cases. This suggests that the selection bias doesn't have significant effects on these parameters of the cost function. The largest difference in magnitudes is in the teaching hospital dummy; the reason is the correlation between the teaching dummy and the location choice. Most teaching hospitals operate in urban areas; because urban areas are lower cost, the raw results suggest that teaching hospitals are lower cost. However, the treated results control for that effect. Therefore, though the raw results indicate that teaching hospitals are more costly than non-teaching, they slightly diminish the true effect.

It's difficult to interpret the coefficients of the outputs and input prices because of the structure of the cost function. To address this problem, Table A.6 presents the cost elasticities of the two output variables and the price of capital. It includes the elasticities calculated at the mean as well as the 25th, 50th, and 75th percentiles. As expected, all elasticities are positive. At the mean, admissions and outpatients increase costs more than the price of capital.

However, the positive coefficient on the CMI variable matches our expectations that more severe patients require more resources to treat. Also, it's interesting to see that whether a hospital belongs to a system doesn't significantly affect the costs. This runs counter to the purported rationale for increasing hospital concentration.

Table A.7 shows the coefficients of the efficiency variables. It is again divided into two columns corresponding to the untreated (left) and treated (right) results.<sup>6</sup> As expected the treated results do depart from the raw results, especially with regards to ownership and location.

If we focus first on the demographic controls, we again see that controlling for

---

<sup>6</sup>Coefficients in Table A.7 describe how the variable shifts the distribution of the efficiency-explained error term. Higher values denote a positive marginal effect on *inefficiency* and a negative effect on *efficiency*.

the selection bias doesn't affect most of the parameter estimates. Though in both specifications, higher concentration reduces efficiency, the effect is smaller in the treated results. This, like teaching can be explained by the correlation of HHI with market size. In larger markets, the HHI will likely be smaller than in small markets because there are more firms competing in the former. In many small markets, there's only a single hospital (which leads to an HHI of 1). Because the raw data suggest that larger markets are more efficient than smaller markets, one would expect the raw estimation to generate a positive coefficient. However, with the location correction, market concentration has a smaller effect on inefficiency.

Also, the demographic controls suggest a correlation between health and efficiency; the healthier the people, the less efficient the hospitals.<sup>7</sup> This is possibly caused by some type of returns to scale. Less healthy people need to use the hospital more; perhaps the hospitals improve with the experience or have higher utilization rates.

Table A.7 also provides the variables of interest for this paper. All coefficients are relative to the base outcome—non-profit hospitals in the smallest market. Table A.8 restructures the data into the marginal inefficiency (relative to non-profits). It is included to ease interpretation.

The population dummies, because they're statistically insignificant (in the raw results), suggest that non-profits operate with similar levels of efficiency across all markets. The treated results, however, instead of uniform efficiency, suggest more volatility; in the large markets, non-profits now have a significantly lower level of inefficiency. These results could be a by-product of the competition between so many hospitals in those areas. Indeed, we will see that all three ownership types

---

<sup>7</sup>We take for granted that health status is correlated with affluence and that affluence is correlated with race.

perform better in absolute terms in the largest markets.

Multiplying the coefficients for the interaction terms by the likelihood that a particular ownership type will be in that market will yield the inefficiency of each market. We would expect that larger markets have higher inherent efficiency in the raw results, but these results don't match those expectations. When calculated, size of market has a positive though insignificant effect on inefficiency. It could be possible, however, that the controls erase any effect. When run with only population group as an ordinal variable, we find that there is a small (-0.00245), statistically significant effect. If we add for-profit and public dummies, the effect, though still negative is no longer significant.

Comparing across ownership types, the raw results here match previous studies that show that for-profits are more efficient than both non-profit and public hospitals and public hospitals are more efficient than non-profits; the ordering holds for all market sizes. These results can be seen more easily by comparing the dashed lines in Figure B.7. The lines indicate marginal (compared to non-profit) inefficiency. The dashed lines represent the raw results, and the lower dashed line is for-profit while the higher dashed line is public hospitals. In each market type, for-profits are the most efficient, and public come between the for-profit line and the x-axis. For-profits operating at the lowest cost conforms to expectations for a traditional industry. Public hospital efficiency relative to non-profit is both unexpected and difficult to explain. We do not know of anyone who attempts to account for differences in management or performance between non-profit and public-run enterprises.

The treated results (the right column of Table A.7, the right three columns of Table A.8, and the solid lines of Figure B.7) tell a more complicated story. Even after correcting for the location choice, the same general relationships endure: for-profits are more efficient than public and public are more efficient than non-profit. These

results span small and medium-sized markets, but in the large markets, the point estimates indicate that for-profits are less efficient than public hospitals (although the difference is not statistically significant).

The main conclusion to draw from this is that hospitals do consider the markets' attributes when deciding where to operate and the location is, therefore, endogenous. Estimations that don't consider this endogeneity will have biased results. When the coefficients of interest are subjected to the Hausman specification test, the values are significantly different with an H-statistic of 186.6.

Figures B.8 and B.9 plot the estimated inefficiency for each individual hospital and groups them by ownership type and location. In figure B.8, we can see that for non-profit and public hospitals, efficiency increases as population density increases; for for-profit hospitals, it's noticeable only in the large markets. The second striking fact is that for-profit hospitals are uniformly more efficient than the others in all markets. Only public hospitals in the large markets have comparable efficiency levels.

Figure B.9 shows how inefficiency levels change after correcting for the self-selection bias. In the small markets, only for-profit hospitals' efficiency improves, while non-profit and public hospitals' increase. In medium markets, it is the non-profit efficiency that improves, albeit not drastically, and in the large markets, all ownership types show significant declines in inefficiency. This suggests that the bias has the largest influence on estimates of efficiency in the large markets.

No prior research has explored how the relationships among ownership types might depend on the market conditions. There are two differences between the raw and treated results. In the small markets, for-profit hospitals operate much more efficiently than the raw results indicate.<sup>8</sup> In the large markets, public hospitals

---

<sup>8</sup>These results are not driven by a few hospitals. The distributions of all the for-profit hospitals and public hospitals in small markets are plotted in Figure B.10.



operate more efficiently than for-profit hospitals (statistically no different). The latter fact could be explained by the heavy competition in large markets having larger impacts on public hospitals than any other type. It's conceivable that the profit motive is a strong enough incentive for for-profit hospitals in any setting, but without that motive, only competition can effect similar results.

This is an extension of Caves and Christensen (1980)'s conclusion that when public enterprises face competitive pressure they perform as efficiently as for-profit firms. We see that when public hospitals are in a competitive environment, point estimates show them to be the most efficient, but in less dense areas, for-profit hospitals clearly outperform the others.

This conclusion suggests that governments planning to build hospitals to provide health services to their un-served or under-served populations should consider subsidizing for-profit hospitals instead of managing their own. This approach could provide the desired access to care at a lower cost. Public hospitals already operating might consider either privatizing or subcontracting certain services. In urban areas, these results suggest no new policies, as competition seems to at least partially substitute for ideal policy.

What's counter-intuitive is that neither public hospitals nor for-profit hospitals locate in the areas where they have a comparative advantage minimizing costs. Public hospitals locate in rural areas though they perform best in urban while for-profit hospitals show the reverse behavior. This could be explained by the fact that the estimates are relative to other hospitals in the same area. It could still be true that urban areas are more profitable than rural areas despite the relative differences.

## 2.6 Conclusion

### 2.6.1 Discussion

This is the first paper that attempts to account for the differing motivations of health service providers. Its primary contribution is to point out that different hospital types' different objectives not only influence how they operate but also which markets they serve since they have both the ability and the desire to control which patients they serve.

We find that although raw data suggest that for-profits are more efficient in all markets than the competing ownership types, once location choice is addressed, public hospitals' performance compares favorably with that of for-profits in larger markets. This reinforces the notion that competition can provide a powerful impetus for firms to reduce their costs even without a profit motive.

One criticism of this work is the choice to use stochastic frontier analysis to determine efficiency. While this might be appropriate for for-profit firms, it's not clear that the other ownership types necessarily are trying to minimize their costs. It's conceivable that both non-profits adhere to a utility maximization motivation wherein they try to find an optimal combination of quality and quantity. However, this paper purports to measure the cost-effectiveness of hospitals, if non-profits are choosing not to minimize their costs, it wouldn't affect the results obtained, it would only offer an explanation as to why they perform worse than the other two types.

Despite this legitimate criticism, the results here are important to consider. The hospital industry stands alone as a market containing significant proportions of three ownership types competing with each other. It offers a unique setting in which to test widely held assumptions about for-profit motives and results. Why is their success confined to larger markets? Do the problems inherent with for-profit firms in an

industry characterized by information asymmetry that have been discussed pertain only to small markets? The answers to these questions can push policy-makers to adjust laws to motivate certain types of hospitals in certain settings.

### 3. INCENTIVIZING OWNERSHIP: CAN GOVERNMENT AFFECT FIRM COMPOSITION

#### 3.1 Introduction

Many economists have argued that certain industries (such as healthcare) have fundamental idiosyncrasies that prevent for-profit firms from enhancing social welfare as they do in “normal” industries. Foremost among these industries is healthcare. In these environments, it may be optimal to impel non-profit enterprises and impede the for-profit. In this paper I determine whether the US government has the ability to shape the composition of competitors in the private Medicare market. I find that by adjusting the payment formula, it can control that particular outcome.

Another contested issue is whether non-profit firms act in the interest of society at large or for non-altruistic and selfish motives. Admittedly, the answer likely varies from industry to industry and firm to firm as to the degree of altruism, but Medicare Advantage could provide us a context in which we can find some evidence. If non-profit firms are acting in the interests of society, then high profit-margin environments, on average, should not attract their participation. It might be the case that they pursue high profits in order to cross-subsidize less affluent areas, but on average, those two effects should cancel each other out to some extent.

However, if profit margins have a greater effect on non-profit participation than for-profit participation, then this suggests that non-profits are not behaving as magnanimously as governments desire. Additionally, the preferential tax treatment could explain small differences in effects between the two enterprises.

I do this by using a model of firm entry devised in Berry (1992) that includes the ability to treat individual firm characteristics as explanatory variables. In this case I

used both the non-profit status of the firms and its interaction with the government capitation payments to the plans. If the interaction term is not zero, the result implies that non-profit firms respond differently to the payment schedule, and the government can to some extent control the composition of the firms. The magnitude of the deviation from zero will represent how sensitive the composition will be.

I apply this model to publicly available datasets: the Area Resource File, the Medicare Advantage Enrollment data, and the Medicare Advantage Plan Directory. The latter two are available from the Centers for Medicare and Medicaid Services, though historic plan directories are no longer present. The Enrollment data provides enrollment numbers by county and plan, while the directory lists organization information for each plan. The Area Resource File is provided by the Department of Health and Human Services. It contains detailed demographic and health-care related data for each county.

This paper is the first to apply the Berry (1992) framework to health insurance and the first to explore how non-profit insurers in Medicare might respond differently to the capitation payments. While many studies have examined how non-profits might effect different outcomes than for-profits, few have analyzed what factors might affect the composition of firms. It is also the first to use firm-level analysis instead of the plan-level analysis featured in previous papers. This lends additional credence to the analysis of the Medicare Advantage market which has been studied previously.

Few studies are concerned with either the factors that explain the presence of non-profit firms or the effects that non-profit firms have on an industry. With respect to the latter, a few studies have concentrated on the insurance industry in particular. Dafny and Ramanarayanan (2012) found that when a non-profit insurer that dominates a market converts to a for-profit insurer, premiums for employer plans increase substantially. These results suggest that policy-makers may be interested in trying

to push markets one way or another.

The cost of Medicare has recently been a hotly debated issue, and, specifically, the payments made to private plans under Medicare have been criticized for being too high. Previous administrations have increased capitation payments to attract entrants and create a market with multiple competitors in each county so that seniors across the country will have several choices. Research into the topic has supported that argument. Opponents, however, argue that the objective of the private plans was to reduce the costs of Medicare, but paying them such high prices counteracts any savings. If non-profit firms offer superior quality and/or lower prices and if lower payment rates can tilt the industry toward them, then a less costly, higher value product would result.

Several states have laws that favor formation of non-profit enterprises. One indirect example would be levying high corporate tax rates. In these environments, non-profit firms would operate at a relative advantage. This advantage for non-profits would allow them to, conceivably, charge lower prices to consumers or offer a higher quality of service, or both. If for-profits are truly unable to increase welfare in certain industries, then governments should do what they can to accommodate alternative organization types. Doing so could reduce the competitive burden that may prevent non-profits from entering the industry.

### 3.2 Literature

Exploring the determinants of entry decisions has long been of interest to Industrial Organization. Bresnahan and Reiss (1991) developed an econometric model of entry that did not employ price or cost margin information. Instead, it relied only on observed entry in markets and the size (and other demographic information) of the markets. Their basic premise was that larger populations should be able to sup-

port increasing numbers of firms and that those thresholds can be estimated. Their model hinges on the assumption that additional firms will reduce market prices, and, therefore, profit margins until the next potential firm would earn negative profits.

Berry (1992) improved on the Bresnahan and Reiss (1991) framework by allowing for firm heterogeneity. Adding this complication, however, required that he account for multiple equilibria based on which firm types decided to enter; it could be possible that different orders of entry may result in different numbers of equilibrium firms. By restricting the firms' characteristics to affect only their own fixed costs, Berry shows that there can be only one equilibrium number of firms, though the identities of the firms within that equilibrium could fluctuate.

Mazzeo (2002), Seim (2006), and Ciliberto and Tamer (2009) each offered alternative approaches to the previous two models. Mazzeo (2002) replaced firm heterogeneity in fixed costs with the ability for the firms to product differentiate. He found that the quality of a firm's competitors does change their effect on profits. Seim (2006) offers a related model of entry wherein instead of firms choosing different quality types, they choose physical locations within markets. Her results support the Bresnahan and Reiss (1991) approach when the product is homogeneous.

Ciliberto and Tamer (2009) broadened the Berry framework to obviate order of entry assumptions. Their model also estimated other-firm effects on profits. It provides more versatility than Berry (1992) because it allows, for example, Southwest to have a different effect on American's profits than United has and vice versa. They accomplished this by accounting for the uniqueness of equilibria in their simulation. By doing so they were able to estimate a lower bound and upper bound of probability for each possible outcome. As such, they only partially identify the parameters.

Each of these methods has its advantages. In this paper I will focus mainly on the Berry (1992) methodology, but I'll also compare its results against the results

obtained from both the Bresnahan and Reiss (1991) and Ciliberto and Tamer (2009) frameworks.

Several health economists have been interested in the Medicare Advantage Program, and, in particular, the decision of firms to enter markets. Both Town and Liu (2003) and Maruyama (2011) used structural models to study the industry. Their main objective was to determine the welfare impacts of the program.

Cawley, Chernew and McLaughlin (2005) applies the Bresnahan and Reiss (1991) framework to estimate how government Medicare Advantage payments affect the number of providers in a market. They predicted (and found) that higher payments would increase the profits of the plans, and, thereby, increase the number of plans available. The Medicare Advantage market is an especially appropriate market for this type of analysis because of the well-defined market areas and the availability of data for both the markets and the plans.

Only Maruyama (2011) accounted for the different ownership status of some firms. By including non-profit status as a dummy affecting fixed costs in the firm profit equation, he found that non-profits faced lower fixed costs than for profit firms. He explained this by appealing to the non-profits choosing markets with less consideration of profitability, and that these markets have lower fixed costs associated with them.

In addition to including the ownership status of the hospital as Maruyama (2011) and Town and Liu (2003) did, my paper will also include several types of insurance plans—HMO, PPO, etc. Additionally, instead of treating each plan as a potential entrant, it aggregates plans owned by a single firm and treats that as one entrant. Finally, the core contribution is the inclusion of an interaction between non-profit status and capitation payment rate to determine how payments influence the ownership composition of firms.



### 3.3 Industry Background

When Medicare was created in 1965, it comprised only two parts: Part A which mostly covered hospital costs and Part B which mostly covered outpatient procedures. In 1985, Medicare Advantage began to take form. Part C of Medicare was intended to expand the choices available for seniors on Medicare. Instead of being confined to the publicly run program, seniors could choose to enroll in HMOs authorized by the government to serve the Medicare population. The private plans would be required to cover the same benefits as Medicare Part A, but could structure its payment system any way it desired. Beneficiaries would still be required to participate in Part B and pay the additional premium.<sup>1</sup>

If a beneficiary chose to enroll in one of the private plans, Medicare would pay the plan annually 95% of the average cost for the beneficiaries living in the same county. Between 1985 and 2009, the program changed names first to Medicare+Choice then to Medicare Advantage. Congress also changed the formula to determine how much the plans would be paid for the beneficiaries who enroll with them. They added risk-adjustment factors (gender, age, and medical history) to the baseline payment, but they also modified how the baseline was determined. Instead of using 95% of the Fee for Service (FFS) rate as they did before, the baseline would be the the maximum of the FFS rate adjusted for inflation or a minimum rate based on geography. Congress expected and intended that these increased rates would persuade more private plans to participate.

Insurance companies that participate Medicare Advantage create insurance plans to offer to seniors and request approval from the Centers of Medicare and Medicaid Services (CMS) to offer those plans in counties. Once approved, the insurance com-

---

<sup>1</sup>For a more detailed history of the Medicare Advantage program, McGuire, Newhouse and Sinaiko (2011) is an invaluable resource.

pany can offer those plans to the citizens of the counties the plans are approved for. Seniors can go online, enter their ZIP code and see a list of plans that are offered to them. Insurance companies may choose to offer different plans within the same county (perhaps different cost structures; some may charge premiums some may not), and they may choose to offer their plan only in certain ZIP codes, although only 10% of plan-counties choose to do so. Additionally, less than 3% of plan-counties offer their plan in less than 50% of the county's ZIP codes.

In September 2011, 11.9 million (25%) of Medicare's beneficiaries were enrolled in a Medicare Advantage Plan, and that figure fluctuates from state to state and county to county. Insurance plans can be split into both ownership types (for-profit and non-profit) and insurance plan types (HMO, PPO, etc.). Most providers are for-profit providers, and they are much more prevalent in urban areas.

### 3.4 Data

One advantage of studying Medicare Advantage is that CMS provides abundant data and provide convenient market definitions—counties. For this study, these county data will come from the Area Resource File (ARF) provided by the U.S. Department of Health and Human Services Health Resources and Service Administration.

The Area Resource File dataset is an unbalanced time series where some data are available for only certain years. To best combine the two datasets this study focuses on July 2007. I treat all plan types (HMO, PPO, etc.) as identical for now. Though they likely have both different variable cost structures and fixed costs, my empirical model will focus on the difference in fixed costs. I consider ownership and ownership interacted with the Part C payment as the heterogeneous variables.

While the ARF provides the demographic and general health data for the counties, the insurance plan data come from CMS; they provide a list of contracts (an

authorization for an insurance company to serve a particular county), the number of beneficiaries who enrolled under that contract in that county, and other information about the contract such as ownership and service type (HMO, PPO, etc.). Contracts may comprise more than one configuration or “plan” (such as copayment rates or premiums) for the enrollees. Enrollment data are not provided at the plan-level.

Two problems with the enrollment data must be addressed—the presence of firms that have contracted to serve a county but show no enrollment and firms that have enrollees but no contract. The former problem could be caused by firms opening contracts broadly even though they have no immediate plans to compete in those counties but may in the future. Additionally, they could be firms that were once active in the county but have decided to avoid the market indefinitely. I treat these observations as if the company was not operating in that county; even though it has an open contract, the focus of this study is on firms that are actively competing in a market.

Cross-county health care seekers and member migration are primarily responsible for the reverse problem. Because the data are reported by beneficiary address, it may appear as if a plan is active in a market even though it’s not legally able to compete. Because these plans may not necessarily be offered in the new county, I use 0.5% as the cutoff point denoting whether a firm is actively participating in a market; all contracts with less market share are excluded from the analysis.

Of the two problems, the former is much more significant. When the combined enrollment/service area data, there are 209,854 records representing firms either operating in or being contracted to operate in a separate county. Of those, 191,461 (91%) show no enrollees; and 823 (1%) have enrollees but no contract. In addition, 1,909 (1%) of observations have market share less than 0.5% and are excluded.

### *3.4.1 Firm Definition*

Previous analyses have used plan-level data for their research. The problem with doing so is that a single firm may operate multiple plans in a single market. They may offer plans that attract different types of beneficiaries by offering HMOs to the price-conscious, for example. If I treated each plan as an entrant, and firms choose to provide a menu of options to beneficiaries when they enter a market, the results would be biased because each plan may not be entering in order to maximize profit for that plan, but instead, the firm is trying to maximize its profits as an entity.

In 2007, there were 240 parent organizations running plans in the Medicare Advantage program. Among the parent organizations, there were 385 subsidiaries operating a total of 583 plans across the country. 187 (78%) of the parent organizations, operated only a single subsidiary; 26 operated two. Wellpoint, Humana, and United Healthcare each operated more than ten.

The presence of multiple levels of management (plans, subsidiaries, and parent companies) leaves the choice of ultimate decision-maker ambiguous. Do subsidiaries consult with their sibling subsidiaries when deciding where to offer their plans or at least, consider the corporate ownership of plans that are already present in target markets or do they act completely independently? To answer this question, I compared the coverage overlap among subsidiaries of parent organizations to their overlap with other corporations. More specifically, I determined the number of markets where two subsidiaries under the same parent competed and compared it to the number of markets where two subsidiaries under different parents competed. If the numbers were similar, that would suggest that the subsidiaries ignored corporate relationship; if the numbers were different, then that would indicate corporate relationship mattered.

Table A.12 shows the results of this analysis. Ratios near one signify subsidiary independence while those diverging from one signify the opposite. High ratios and low ratios represent different relationships: high ratios suggest that subsidiaries operate in the same markets as each other while low ratios suggest that the subsidiaries avoid each other. Notice how there are many more high-ratio parents than low-ratio parents, and that the largest parents have ratios close to one. This implies that the largest parents are operating differently from small parents.

One explanation for this is that the small parents' subsidiaries are artifacts of the design of the Medicare Advantage program, and they are operating separate subsidiaries that each focus on one type of plan. For example, a small parent might have one subsidiary dedicated to its HMO option and one dedicated to its PPO. In fact, the data bear out that hypothesis for plans with extremely high ratios. Alternatively, large parents are nationally competitive and operate several subsidiaries just to increase their market coverage.

Of the subsidiaries, 325 (84%) operated only a single plan while one of the subsidiaries (operating under United Health Care) operated 39 plans. The plan distribution according to parent company is similarly skewed. Of the 240 parent organizations, 160 (67%) operated only a single plan, while 90% operated three plans or fewer. One parent (again, United Health Care) operated 85 plans.

To account for the different corporate structures, I used the plan's headquarter ZIP code as the decisive information. If the plan's headquarters was the same as the parent's headquarters, I concluded that the parent company was the primary decisionmaker. If two plans had the same parent and different subsidiaries, and the plans' headquarters were located in different ZIP codes, I treated the subsidiary company as the main decision-maker. To avoid complicated nomenclature, I will refer to the decision-maker entity as the *firm* for the remainder of the paper.

After this aggregation, there were 313 firms operating which suggests that there's a mix of both types of parents. Also, no aggregated firm operated more than one subsidiary within any market. On average, each firm operated in 45 markets (median 8) with a minimum of only one market (3 firms) and one firm operating in almost 2500 markets.

### 3.4.2 *Potential Entrants*

Berry's estimation framework requires multiple potential market entrants to define the profitability threshold. This necessitates an algorithm to identify firms that were likely to enter a potential market but chose not to. Maruyama (2011) discusses several options for building this set. Because of the cross-sectional nature of my data, previous entry could not be used. Instead, the pool of potential entrants included actual entrants within that county, actual entrants in neighboring counties, and firms with the highest share of state enrollees (the top three for-profit firms and the top two non-profit firms). I differentiate by ownership type to ensure that both ownership types are possible entrants.

Maruyama includes all plans that operate in the MSA or state; I excluded both. Because I'm including firms operating in neighboring counties, that should account for most of the firms within the same MSA. Additionally, firms are unlikely to enter a market far from their current coverage area just because they are in the same state. Table A.10 provides information on the number of firms both active in each market, and added as potential entrants. It also breaks those firms down by their ownership status.

On average, there are 4.5 firms active in each market, with a minimum of 0 and a maximum of 15. The majority of active firms are for-profit firms. The pool of potential entrants (including those already active) averages 10.6 firms/market. A

larger percentage of the non-active firms are non-profit than is the case for firms actually operating. This is likely due to including the top two non-profit firms in the state as potential entrants in each market. I have also listed the non-active firms by criterion used; the adjacent market criterion clearly makes up the majority of non-active firms. The sum of the two types of non-active firms exceeds the total for all non-active plans, because some firms satisfy both criteria.

Figure B.11 shows the distribution of both active and non-active plans. The distribution of both types is skewed toward zero. Figures B.12 and B.13 show the number of active and non-active firms in each county, respectively. B.14 shows the percentage of the county's firms that are non-profit. Some states are more varied than others (Colorado, Idaho) while others are uniformly different (Minnesota and Tennessee). This indicates that there may be state-level policies that advantage non-profit firms. I will control for the uniformly different states with dummy variables.

### *3.4.3 Payments*

Figure B.15 shows the relationship between base capitation payments to plans and how many firms compete in that market. Not only is the relationship positive, but it is also very strong as the number of competitors rises very quickly with the base payment. Increasing the payment from \$700 to \$800, for example, raises the number of competing firms from two to thirteen. However, the strength of the relationship diminishes with higher payments. As the figure shows, with higher payments, the number of additional firms does not increase as rapidly.

Figure B.16 shows the relationship between base capitation payment and the composition of firms in the market (percentage of firms that are non-profit). There is a slight, but noticeable, trend showing that higher payments attract relatively more for-profit firms. This suggests that for-profit firms are more responsive to

the mechanism suggested in previous research (and by policy-makers) that higher payment rates attract more firms.

#### 3.4.4 Moments

Berry's framework requires both firm-level and market-level moment conditions. For the firm-level moment conditions, I interact the firm-level error (the difference between the probability of entry and actual entry) with all market variables and firm variables as well as state market share, area market share, and HHI calculated from the market shares. For the market-level moment conditions, I interact the market-level error (the difference between the predicted and actual number of firms) with all market variables, the number of firms operating in area, size of market in relation to size of area, and HHI. Because there's a varying number of potential entrants for each market, I use the moment conditions of the three firms with the highest market share in the area.

### 3.5 The Model

I use Berry's profit specification. In market  $i$ , firm  $k$ 's profits can be described as

$$\Pi_{mj} = Y_m\lambda + Z_m\alpha + \delta \ln(j) + \rho u_m + W_{mj}\beta + \sigma u_{mj} \quad (3.1)$$

In this equation,  $Y_m$  represents market-level demographic characteristics to reflect demand and  $Z_m$  includes market-level cost characteristics.  $j$  denotes the number of insurers operating in the market and accounts for the competitive effect.  $u_m$  is a market-level error term meant to capture unknown market-level shocks such as density of hospitals.  $W_{mj}$  includes firm-level characteristics, and  $u_{mj}$  is a firm-level error term.

$u_m$  and  $u_{mj}$  are distributed i.i.d. standard normal across firms and markets. This



suggests that a shock to a firm in one market won't affect its operations in another. While probably true for small shocks, there are certainly cases where a firm's success in one market will affect how it runs in others. For example an insurer in Chicago might face an unexpected demand for services and direct resources away from other areas. It also precludes a shock to a single firm affecting other firms in the market, for example, if an insurer's main provider was forced to shut down would increase demand for the other insurers. Also, I impose  $\sigma = \sqrt{1 - \rho^2}$  to ensure the variance of  $\epsilon_{ik} = u_{io} + u_{ik}$  equals one.

### 3.6 Estimation Procedure

Following Berry (1992), I use a simulation estimator to determine the coefficients  $\beta$ ,  $\rho$ ,  $\alpha$ ,  $\delta$ , and  $\sigma$ . The simulation procedure begins by drawing M+K random values from a standard normal distribution. Each market has a single disturbance value as well as each firm in each of those markets. To begin the simulation, I guess a coefficient vector to use. I determine  $Z_{ik}\alpha$  and order the results by decreasing profitability for each market. By market, the number of firms with higher values will be N. I can then calculate the remainder of Equation 3.1.

The number of firms with profits greater than zero then will be the predicted number of firms for that market. I repeat the procedure R times and average the results for the frequency estimator. The error can be found by subtracting this value from the observed number of firms operating in the market. In addition to this market-specific error, I calculate firm-specific error by a similar procedure. For the F firms with the highest market share in the neighboring markets, I determine whether or not their estimated profit is greater than zero R times and take the average. I subtract the average from one if it did enter and zero if it did not. The product of these errors and a set of instruments is minimized by changing the parameter

vector. In subsequent steps I weight the criterion function by the covariance matrix calculated from previous estimations.

### 3.7 Results

The estimated coefficients are presented in Table A.13. The absolute magnitudes of the coefficients have no real-world meaning, but the signs and relative magnitudes are relevant. The signs indicate whether that particular variable increased the probability that additional firms would enter.

For the payment amount, this suggests that the higher the payment, the more firms enter the insurance market; this reinforces previous research on the topic. It also coincides with the relationship we see in Figure B.15. Notice also, that the magnitude of the effect is the largest of all the coefficients, but keep in mind that this is the effect of increasing the capitation payment by \$1,000.

The coefficient for the interaction of payment and non-profit status is also positive suggesting that non-profit firms are more sensitive to increases in the capitation payment than the for-profit firms. One explanation is that non-profit insurers are more likely to be the marginal firms. For-profit firms probably enter the lower-paying counties and take advantage of the cream-skimming potential while non-profits are less adept at doing so, so they can only compete in counties with higher payments. This relationship is contrary to what we see in Figure B.16 because Figure B.16 does not control for costs.

The capitation payments can also be considered as a proxy for profits. In essence, the capitation payments represent revenues while the reimbursement levels represent the cost for the plan to serve the average person in the county. Because I'm controlling for the latter (as well as demand and competitors), any change in the former should represent a change in profits.

The fact that this coefficient is positive means not only that non-profits are more responsive to the level of potential profit in a market than are the for-profit firms, but also must mean that they are attracted by the higher margins. This suggests that these non-profits are in fact behaving as for-profits. They enjoy the added benefit, however, of lower tax levels. With lower levels of taxation, the non-profit firms retain a larger percentage of any profits they accrue, which might account for the additional responsiveness.

Though the effect is statistically significant and positive, the economic significance is rather small. The coefficient is less than 1% of the magnitude of that of the capitation payment, suggesting that though positive, the effect is not remarkable. However, if the only advantage non-profits have over for-profits is a lower tax liability, the size of the effect wouldn't be surprising.

The coefficient for the number of competitors is also negative. This reflects the fact that the more firms already active in a market, the less profitable a new entrant will be, and, therefore, the less likely a firm will enter the market. This estimate conforms to expectations.

As for the remaining parameters, the more people who are using Medicare, the more profits firms can earn which induces firms to participate in the market. This, of course, represents the demand side of the market and matches previous results. Conversely, the expectation of growth (percentage growth in enrollment) actually suppresses entry which contradicts previous results.

Increased reimbursements imply that health costs are higher in those markets, which not surprisingly decreases the likelihood that insurers would want to participate in that market, especially given the fact that they must charge each patient the same premium. Income and % white collar both decrease insurer participation.

Finally, distance from headquarters decreases a firm's likelihood of entering a

market; this fact supports the idea that most firms participating in this market do so at a local level, and the costs of negotiating contracts in remote locations outweigh the potential increases in revenues.

Figures B.17 and B.18 show the model's predictions for the number of total firms operating in each market and the number of for-profit firms in each market, respectively. The line included is a 45 deg line. Though neither looks particularly accurate, the market prediction seems to be better than the for-profit predictions. The market predictions do seem to increase as the actual number of firms goes up, but the trend is considerably flatter than a 1 to 1 correlation. In Figure B.18, there seems to be little to no correlation.

### 3.8 Conclusion

Non-profit insurance companies play a significant role in the Medicare Advantage program, but their intentions, whether altruistic or not, are not clear. Understanding how they make entry decisions will help elucidate what drives their other decisions. In this paper, I have found that they are more responsive to increases in the Medicare Advantage capitation payments than are the for-profit firms competing in the same industry. This suggests that their behavior is more akin to the profit motive than the goal of providing health care services to more needy consumers.

If non-profits are not acting in the public interest, the preferential tax treatment would no longer be necessary. Of course, this kind of change should not be undertaken lightly. Non-profits in many industries (including Medicare Advantage) provide an important service. There are many non-profit organizations who are actively attempting to promote and enhance public welfare, and they should continue to be encouraged.

Additionally, this research provides the government with a mechanism to either

promote or suppress non-profit participation in the Medicare Advantage market, depending on their policy objectives. Higher payments increase the number of non-profit plans relative to for-profit plans. Previous research has found that increased payments also increase total number of competitors in a market; if non-profits do in fact act in the public interest (either in contradiction to this research or after future policy changes), then this research provides a mechanism to increase non-profit participation in markets.

## 4. THE WELFARE EFFECT OF MEDICARE ADVANTAGE: A MICRO APPROACH

### 4.1 Introduction

Policymakers are increasingly exploiting market forces when designing systems to achieve their political objectives. The most famous example is the creation of the cap-and-trade system applied to sulfur dioxide emissions in the 1990 Clean Air Act. Policymakers decided their approach should align firms' incentives with public welfare instead of dictating particular outcomes.

From school choice to automobile emissions, examples of legislators embedding their goals within the constructs of economic insights abound. When done thoughtfully, they can reduce the adverse effects of regulations and enhance welfare.

This approach to public policy can manifest in several ways. One possibility is to allow private firms to compete with publicly-run programs. Charter schools and package delivery firms such as FedEx and UPS are examples of this method. Another example is Medicare Advantage. In Medicare Advantage, private insurers compete with each other and the government (in the form of Medicare) to offer health insurance to people over 65. Advocates argue that the presence of competition pressures the government to better serve the public by offering them options they may prefer. If citizens prefer the public option, then this points to a market failure for that particular industry (assuming the public option is competing on relatively equal footing), while if citizens forgo the public option, this implies that it is poorly run at worst or unnecessary at best.

Given an additional option, if someone prefers it, its existence has increased social welfare since that one person is better off with it. However, if the cost of providing

that option is greater than the increase in welfare, it is better not to offer it. This conflict is at the heart of the debate over Medicare Advantage. In 2003, politicians enamored with the power of competition (possibly overly-enamored) increased the payment rates above those of traditional Medicare in an effort to increase private competition in the program. In 2009, Medicare Advantage paid 14% more than traditional Medicare per enrollee.

Opponents argue that the difference offsets the potential welfare from increased choice and have passed laws to reduce the disparity. Thanks to the Medicare Improvements for Patients and Providers Act of 2008, that difference fell to 9% in 2010 and is expected to fall to only 2% by 2017 Biles et al. (2012). Supporters of the Medicare Advantage program decry this reduction and argue that it will result in the exodus of private firms and reduction of choices for seniors. These positive consequences are not disputed by those who want to reduce costs, but the debate is over the normative results.

This strain of research is important both to the current debate over the levels of "reimbursements" to insurance companies participating in Medicare Advantage, but also to insurers for the general population. Medicaid recipients also have the ability to choose private plans to provide their insurance. With the expansion of Medicaid being undertaken by many states under the Affordable Care Act as well as the likely expansion of Medicare as the over-65 population swells in the next few decades, it is important to determine an optimal level of competition in these markets and the costs of reaching those levels.

More broadly, as the government and society evolve, it is likely that in some industries, the public will want government to become more involved while in others, they will desire the addition/expansion of private choices. Private firms competing with the government with any level of success enhance social welfare and should be

encouraged as long as the benefits outweigh the costs.

I find that for the year 2005, the Medicare Advantage program had a net cost to the government of \$11.11 billion but increased welfare by \$18.87 billion. Therefore, the net increase in welfare was \$7.76 billion. This is evidence that the Medicare Advantage program was an efficient use of tax-payer dollars despite paying, according to my data, 28% more per beneficiary (this figure is higher than the figures above because it also accounts for advantageous selection into Medicare Advantage).

## 4.2 Literature

Small and Rosen (1981) provided the framework used to estimate the welfare generated by discrete choices. Their methodology has been applied to innumerable situations. They proposed it in the context of estimating the welfare loss from increased taxation, but it has been adapted to estimate the welfare effects of both quality changes with choices and the loss (or gain) of choices themselves. This approach is suited for the analysis of many decisions consumers make—automobiles, homes, cereal, etc., any circumstance when they choose a discrete unit of a good instead of the quantity of a particular good.

There have been several applications of this technique to estimate the consumer welfare from Medicare Advantage in particular—most notably Town and Liu (2003) and Maruyama (2011). Additionally, Hall (2010) and Dunn (2010) contributed to the evidence with regard to this program. Though Maruyama and Town and Liu included both demand and supply sides to their model, all four used a similar approach to estimate the demand-side, and, hence, the change in welfare.

All four used the aggregated method developed by Berry (1994) to estimate consumer choice and welfare. Using this approach, they were able to take advantage of the enrollment data provided by the Centers for Medicare and Medicaid Services



(CMS) to calculate market shares of each Medicare Advantage insurance plan in each county and therefrom estimate a discrete choice model. They then used those estimates to determine indirect utility and the change in utility from removing Medicare Advantage.

Instead of using the aggregate enrollment data, I will use survey responses of Medicare beneficiaries to estimate the effect of individual and plan characteristics on their choice of whether to participate in Medigap, Medicare Advantage, or remain with traditional Medicare. In previous literature, the authors treated Medicare with supplemental Medigap as the outside option. This may bias their results against Medicare Advantage as it assumes all beneficiaries not in Medicare Advantage participate in the more comprehensive Medigap.

Maruyama, Hall, and Dunn all found the net benefit of Medicare Advantage (increased welfare minus operational costs) to be close to \$10B/year. Hall finds that figure to be true from 1999-2002, Dunn in 2007, and Maruyama in 2003 and 2004. All four authors included estimated profits from the private plans as well. The consistency of these results despite the differences in methodology implies either their accuracy or that their chosen method of estimating demand overwhelmed the less significant estimation decisions in their approach. By estimating based on survey responses instead of market shares, I provide evidence in favor of the former explanation.

## 4.3 The Model

### 4.3.1 Insurance Plan Choice

Seniors (denoted  $i$ ) choose their insurance plan (denoted  $j$ ) based on many characteristics: premium, copay, deductible, out of pocket spending maxima, the size of the network, the fees for going out of network, and the customer service of the

insurer. It will also depend on other patient characteristics such as income, gender, etc.

$$u_{ij} = u(oop_{ij}, network_j, service_j, X_i) \quad (4.1)$$

The out of pocket fees will be some function of the premium, copays, and deductibles with the patient's health as well as the network (the patient will have to pay higher amounts if they go out of network).

$$oop_{ij} = oop(premium_{ij}, copay_{ij}, deductible_{ij}, health_i, oopmax_{ij}, network_j) \quad (4.2)$$

#### 4.3.2 Program Choice

Seniors' choice of which program to utilize is very similar to their choice of insurance plan. They consider the same factors as previously.

$$u_{ij} = u(oop_{ij}, network_j, service_j, X_i) \quad (4.3)$$

$$oop_{ij} = OOP(premium_{ij}, copay_{ij}, deductible_{ij}, health_i, oopmax_{ij}, network_j) \quad (4.4)$$

The equation I'll estimate will be

$$u_{ij} = \beta_1 OOP_j + \beta_{health} X_i^{health} + \beta_x X_i^{demo} + \epsilon_{ij} \quad (4.5)$$

which leaves network and service as components of the error term. Because both would be correlated with the costs of insurance (probably distributed through premi-

ums, deductibles, copays, etc.), endogeneity would exist. However, the endogeneity would be constrained because of the aggregated nature of the decision. Because we are only looking at whether they choose Medicare, Medigap, or Medicare Advantage, correlation between variables would be limited. For example, the Medicare and Medigap networks are largely the same, so that would not affect the patient’s choice between the two.

### 4.3.3 Implementation

Actual estimation will employ a conditional logit model where the choice variable is the program (traditional Medicare, Medigap, and Medicare Advantage). It takes the form

$$u_{ij} = \beta_x X_i + \beta_{Z_{ij}} Z_{ij} + \epsilon_{ij}$$

where  $Z_{ij}$  is a set of choice-specific variables,  $X_i$  is a set of beneficiary-specific variables, and  $\epsilon_{ij}$  has a generalized extreme value error distribution.

$Z_{ij}$  comprises out of pocket (OOP) costs as well as a proxy for network size. For those who have provided their OOP costs, those are entered directly into the estimation; because respondents can only provide OOP costs for the program they chose, other OOP costs must be imputed. For Medigap, the average OOP costs for Plan F is used for those not participating. For traditional Medicare and Medicare Advantage, estimates from Medicare.gov are used.

The network variable is calculated with a similar method, but exclusively from the survey data. To proxy for the size of the network, I use the response to the question: "How many minutes does it usually take to get to Dr.’s office?" I then calculate means for each program to fill in the missing observations.

$X_i$  includes demographic variables such as age (age squared), gender, education,

marriage status. It also includes dummy variables indicating whether the respondent was currently employed and whether he was a veteran. Finally, it includes the categorical response (on a scale 1-5) to the question "How would you compare your health to others the same age?"

#### 4.3.4 *Consumer Surplus*

To estimate the consumer surplus from having an additional option in a discrete choice model is a pretty straight-forward process. One need only calculate the change in indirect utility and convert it to a monetary figure. In this case, the change in indirect utility can be expressed as

$$\Delta E(V_i) = \ln \left( \sum_{j=1}^{J^1} e^{V_{ij}^1} \right) - \ln \left( \sum_{j=1}^{J^0} e^{V_{ij}^0} \right)$$

where the subscripts 0 and 1 represent the actual state (with Medicare Advantage) versus the hypothetical state (without Medicare Advantage), respectively. This value is then multiplied by the inverse of the marginal utility of income to obtain the expected welfare (in dollar terms) added by Medicare Advantage. In this case, I will use the coefficient for the out of pocket costs as the marginal utility of income. This calculation is done on a per-person basis and will be weighted to represent the full Medicare population.

#### 4.3.5 *Net Costs of Medicare Advantage*

The net costs are calculated using CMS's enrollment data. For each county, the base capitation payment is multiplied by the number of seniors enrolled in a Medicare Advantage plan to obtain the base cost. For privacy reasons, CMS aggregates counties with fewer than 11 seniors enrolled in Medicare in Medicare Advantage into a single observation. For those beneficiaries, I use the average base payment for the

state.

CMS reports enrollment information on a quarterly basis. To obtain the full year’s estimate, for each county, values are interpolated for the months not reported, and figures for all twelve months are combined.

To estimate the costs had all of the Medicare Advantage enrollees participated in traditional Medicare instead, I take the per capita costs for traditional Medicare enrollees for each county. To account for the different risk profiles of traditional Medicare and Medicare Advantage, I use the risk scores reported by CMS for each county and program (and the average risk score for the state for counties with fewer than eleven enrollees). These risk scores are calculated for each Medicare beneficiary based on the diagnoses he receives. Those scores are then averaged for the populations of both programs. The higher the score, the less healthy the beneficiary is, generally. To correct for this differential, I multiply the base payment by the ratio of the risk scores for each program in each county.

## 4.4 Data

### 4.4.1 Overview

The data used come from the Medicare Current Beneficiary Survey (MCBS). The MCBS is an annual survey of Medicare’s beneficiaries meant to understand the quantity of their care, access to care, as well as how that care is delivered. It comprises two modules—the Access to Care and Cost and Use. The former surveys the beneficiaries’ interaction with the health care industry—specifically, insurers, hospitals, and doctors. Contrarily, the latter focuses on particular episodes such as services performed. This analysis will be confined to the Access to Care module.

Additionally, the data will be from 2005. 2005 was the last year before Medicare Part D went into effect, which gave all beneficiaries a new entitlement to prescrip-

tion drug services. Prior to 2006, prescription drugs were only covered by certain Medigap and Medicare Advantage Plans; those in traditional Medicare sought their medications independently.

The sample includes a total of 15,769 respondents (out of about 42 million total beneficiaries). Table A.14 provides some summary statistics for all respondents as well as by which branch of Medicare the respondent utilizes. The mean respondent earns less than twenty thousand dollars/year and reports better than average health (the health figure is a self-reported rating of health on a scale of 1-5). About 78.8% of the respondents are white, which is higher than the nation at large. A little under half the sample is married and over half are female. Less than a quarter are veterans. Unexpectedly, less than 70% of the respondents finished high school, while 25% finished college.

About half of the respondents use Medigap, about a third traditional Medicare and over ten percent Medicare Advantage, making it the least-used option among the three. (By 2013, between 20 and 25% of beneficiaries belonged to a Medicare Advantage plan). Those who opted for non-traditional Medicare were older, wealthier, and better educated than those remaining. They also reported worse health. Demographically, white seniors were more likely to eschew traditional Medicare. Veterans and women also opted for Medigap/Medicare Advantage.

#### *4.4.2 Medigap*

Figure B.21 shows the prices for the different plans respondents pay. It includes only respondents who purchase their plans directly, not through an employer, union, or AARP. The mean price paid for a directly purchased Medigap plan is \$1,778/yr (the median is \$1,659). In the sample, there are 11,814 senior/Medigap plan combinations representing 8,579 actual respondents, each with an average 1.377 plans.

(Almost 75% of beneficiaries had only one plan, 20% have two, 5% have three, and 2 % have 4 or 5 as can be seen in Figure B.20).

As you can see from Figure B.19, Plan F is the most popular of the Medigap plans. 42.8% of people with only a single plan had Plan F (and 44% of respondents with at least one plan participate in Plan F).

Of the people who participate in only a single plan, 78% paid at least part of the premium. On average, they paid \$1,928/yr. Because this is higher than the figure for those purchasing their plans directly, it is possible that those who were subsidized by a third party opted for more generous plans and end up paying more (it's also possible that these beneficiaries had higher-paying jobs when employed concomitant with more generous benefits packages).

#### *4.4.3 Medicare Advantage*

As with the traditional Medicare and Medigap, the MCBS Access to Care Module survey also surveys beneficiaries as to their utilization of Medicare Advantage. Additionally, however, to estimate the net costs of the Medicare Advantage program, I take advantage of the CMS enrollment data with regards to Medicare Advantage plans in 2005 as well as the estimates of risk scores and calculations they provide for both Medicare Advantage and traditional Medicare.

With regards to the survey, about 12% indicated that they participated in Medicare Advantage in that they were enrolled in a Medicare HMO. Figure B.22 breaks down the number of Medicare Advantage plans that were available to each beneficiary (whether they participated or not). More than 75% of beneficiaries had the option of participating in Medicare Advantage, and more than half ( 57%) had at least two competing plans to choose from. Of those who did participate, 76% chose a plan that included prescription drugs, which suggests that this is a powerful incentive

for participation, especially in the years before Medicare Part D.

As to the price of Medicare Advantage, about 63% of plans did not charge an additional premium. Of those that did, contrary to Medigap, 88% of respondents paid for it directly. Figure B.23 lays out the distribution of prices for Medicare Advantage plans used by the respondents. The highest premium was \$5400, and the minimum non-zero premium was \$20. The (non-zero) mean was (\$958) \$353, and the (non-zero) median was (\$780) \$0.

The CMS enrollment data provide another perspective to the Medicare Advantage program. These data are on a county basis and provide the total enrollment in the Medicare Advantage program for each county. They also include the base capitation payment paid for each enrollee for that county. As a check on the take-up of Medicare Advantage, Figure B.24 shows the penetration figure from December 2004 through December 2005. As you can see it's gradually increasing from 12.7% at the end of 2004 to 14.0%. These figures are a little higher than those suggested earlier from the MCBS. This can be attributed to how I assigned respondents to a program. If respondents indicated that they participated in both Medigap and Medicare Advantage, if they were in Medicare Advantage, for less than half the year, they were assigned to Medigap instead. For the month of December, about 14% of respondents indicated they participated in a Medicare Advantage plan, which matches the CMS data.

To account for the reported selection of healthy individuals into Medicare Advantage, I use the risk scores provided by CMS for each county and each program to correct for the costs. Figure B.25 shows the distribution of the ratio of Medicare Advantage risk to traditional Medicare risk for each county in 2005 (ratios of less than one suggest that Medicare Advantage enrollees are in better health than traditional Medicare).



The mean (weighted by the number of seniors eligible for Medicare) risk ratio is 0.945, suggesting a small but visible selection problem. Crenshaw County Alabama has the lowest risk ratio (0.118) while Moore County, Texas has the highest (7.6605). About 60% of counties exhibit positive selection into Medicare Advantage.

#### 4.5 Results

Table A.15 provides the estimates for the coefficients. It is organized with the choice-specific variables at the top, and the individual-specific at the bottom. Traditional Medicare is the reference outcome. Surprisingly, the coefficient for the cost variable is positive, indicating that higher cost plans increase utility. This is the result of two factors: first, the method in which missing data were filled did not include premium data for individuals in Medicare Advantage, only out of pocket estimates provided by CMS. This results in these estimates of OOP being sub-optimal. Secondly, if beneficiaries have different tastes for risk, those tastes may skew our estimate of the coefficient for cost. The wait time for getting to a doctor decreases utility. This is as expected.

As for the individual-specific terms, we can see that higher income beneficiaries are more likely to opt for something other than traditional Medicare, with Medigap being relatively more attractive. This fits with prior expectations of wealthier individuals choosing to and being more able pay for supplemental coverage. Additionally, this suggests that more-educated beneficiaries are more likely to better understand their options.

Older beneficiaries also opt for the supplemental coverage, especially Medicare Advantage; this is possibly due to experience with the program. Older beneficiaries are more likely to join Medicare Advantage than Medigap. Time limits for employer subsidies could explain this.

Married beneficiaries and veterans are more likely to choose either trans-traditional Medicare program at statistically similar levels. Also, the employed are more likely to stick with traditional Medicare. Their employer probably provides their own health insurance coverage outside of Medicare which reduces the need for any kind of supplement.

Another surprising outcome is that those in trans-traditional Medicare programs report relatively worse health, with Medicare Advantage users reporting the lowest level. This contradicts the risk ratio results discussed previously.

#### *4.5.1 Net Costs of Medicare Advantage*

With the results from the discrete choice model we can estimate the welfare addition from the existence of the Medicare Advantage program, by first calculating the figure for each individual, and then extrapolating those estimates to the entire Medicare population.

Figure B.26 shows the distribution of respondents with regard to how much loss in consumer surplus comes from removing Medicare Advantage as an option. The mean loss is \$597. The most any respondent stands to lose is \$1,600 and the smallest loss is about \$1; the median is \$660. Table A.16 shows the estimated welfare increase both for the whole sample and broken down by program. Reassuringly, the highest mean and median increases are for those enrolled in Medicare Advantage already. When extrapolated to the entire Medicare population, the total welfare improvement comes out to \$18.87B in 2005.

From the CMS Medicare Advantage data, I estimate that Medicare Advantage cost a total of \$50.95 billion in 2005. Had those beneficiaries received their coverage from traditional Medicare, it would have cost the government/Medicare \$39.83B for a net cost of \$11.11B. Figure B.27 provides the distribution of net costs (in percentage

terms relative to traditional Medicare) on a county basis. Comparing this figure to the increased welfare, I conclude that in 2005, Medicare Advantage increased national welfare by 7.76 billion dollars, \$1,462 per Medicare Advantage enrollee, or \$198 per Medicare beneficiary.<sup>1</sup>

## 4.6 Conclusion

### 4.6.1 Discussion

In 2011, Medicare explained 13.5% of the federal budget. As the baby-boomers retire, even more money will be redistributed to seniors in the form of health care benefits. Medicare Advantage is a program meant to offer seniors a choice of Medical insurance tailored to their needs in an attempt to reduce costs and ensure quality in traditional Medicare as well as for the numerous retirees who depend on it.

Recently, Medicare Advantage has been the subject of a conflict between the two dominant parties, one of which believes the costs of providing extra options are too high while the other concentrates on providing them with options. As is common in policy debates, neither side provides the full cost-benefit picture.

This paper finds that the existence of Medicare Advantage, though more costly than traditional Medicare, results in a net increase in consumer welfare. Whether the level of payments is optimal, is left up to other researchers. Instead, this paper supports previous research on the costs and benefits by using micro-level survey data in lieu of enrollment figures to estimate the consumer surplus from Medicare Advantage.

As the government expands in some sectors and retracts in others, the framework of its intervention has significant implications for social welfare. By designing systems in which the government is competing with private entities to provide services to

---

<sup>1</sup>The figure is high for MA enrollee because, really, everyone is benefiting from the additional choice, but it's being divided only among those who enroll.

constituents, policy-makers exploit competition to enhance the effectiveness of their prescriptions.

## 5. DISSERTATION CONCLUSION

As my dissertation suggests, the complexity of the health care sector provides an Economist with numerous targets to investigate. I have explored but three of the myriad issues. In summary, I have found that free market principles benefit consumers in the health care sector despite the potential market failures that could exist. For-profit hospitals out-perform other types in the rural areas, but competition compels the public hospitals to perform just as well; there is no welfare benefit to non-profit insurance companies more than the advantages of having additional competition; and the option of private insurance within Medicare provides citizens important opportunities to tailor their insurance to their own needs.

Any segment of the economy that makes up as large a proportion as the health care sector will, of course, include waste and inefficiencies—opportunities to improve its functioning. Both the size and the complexity of health care in the United States will provide future economists and policy-makers perpetual problems and opportunities to provide solutions. Hopefully, this contribution aids that endeavor.

## REFERENCES

- Alchian, Armen A.** 1965. "Some economics of property rights." *Il Politico*, 30.
- Battese, George E., and Sumiter S. Broca.** 1997. "Functional Forms of Stochastic Frontier Production Functions and Models for Technical Inefficiency Effects: A Comparative Study for Wheat Farmers in Pakistan." *Journal of Productivity Analysis*, 8: 395–414.
- Berry, Steven T.** 1992. "Estimation of a Model of Entry in the Airline Industry." *Econometrica*, 60(4): pp. 889–917.
- Berry, Steven T.** 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics*, 25(2): pp. 242–262.
- Biles, Brian, Giselle Casillas, Grace Arnold, and Stuart Guterman.** 2012. "The Impact of Health Reform on the Medicare Advantage Program: Realigning Payment with Performance." The Commonwealth Fund.
- Bresnahan, Timothy F., and Peter C. Reiss.** 1991. "Entry and Competition in Concentrated Markets." *Journal of Political Economy*, 99(5): pp. 977–1009.
- Cameron, A. C., P. K. Trivedi, Frank Milne, and J. Piggott.** 1988. "A Microeconometric Model of the Demand for Health Care and Health Insurance in Australia." *The Review of Economic Studies*, 55(1): 85–106.
- Cardon, James H., and Igal Hendel.** 2001. "Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey." *The RAND Journal of Economics*, 32(3): 408–427.

- Carey, Kathleen.** 2003. "Hospital Cost Efficiency and System Membership." *Inquiry*, 40(1): 25–38.
- Caves, Douglas W., and Laurits R. Christensen.** 1980. *Journal of Political Economy*, 88(5): pp. 958–976.
- Cawley, John, Michael Chernew, and Catherine McLaughlin.** 2005. "HMO Participation in Medicare+Choice." *Journal of Economics & Management Strategy*, 14(3): 543–574.
- Chirikos, Thomas N., and Alan M. Sear.** 2000. "Measuring Hospital Efficiency: A Comparison of Two Approaches." *Health Services Research*, 34: 1389–1408.
- Ciliberto, Federico, and Elie Tamer.** 2009. "Market Structure and Multiple Equilibria in Airline Markets." *Econometrica*, 77(6): pp. 1791–1828.
- Coelli, Tim.** 1995. "Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis." *Journal of Productivity Analysis*, 6: 247–268.
- Cuellar, Alison Evans, and Paul J. Gertler.** 2003. "Trends In Hospital Consolidation: The Formation Of Local Systems." *Health Affairs*, 22(6): 77–87.
- Dafny, Leemore, and Subramaniam Ramanarayanan.** 2012. "Does it Matter if Your Health Insurer is For-Profit? Effects of Ownership on Premiums, Insurance Coverage, and Medical Spending." , (18286).
- Dubin, Jeffrey A., and Daniel L. McFadden.** 1984. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica*, 52(2): 345–362.
- Dunn, Abe.** 2010. "The Value of Coverage in the Medicare Advantage Insurance Market." Bureau of Economic Analysis (BEA) working paper WP2010-11.

- Feng, Ye, Don Fullerton, and Li Gan.** 2005. "Vehicle Choices, Miles Driven, and Pollution Policies." National Bureau of Economic Research Working Paper 11553.
- Fohlin, Caroline.** 1998. "Relationship Banking, Liquidity, and Investment in the German Industrialization." *The Journal of Finance*, 53(5): 1737–1758.
- Folland, Sherman T., and Richard A. Hoffer.** 2001. "How Reliable Are Hospital Efficiency Estimates? Exploiting the Dual to Homothetic Production." *Health Economics*, 10(8): 683–698.
- Goldberg, Pinelopi Koujianou.** 1998. "The Effects of the Corporate Average Fuel Efficiency Standards in the US." *The Journal of Industrial Economics*, 46(1): 1–33.
- Hall, Anne E.** 2010. "Measuring the Return on Spending on the Medicare HMO Program." Federal Reserve Board.
- Kumbhakar, Subal C., and C.A. Knox Lovell.** 2000. *Stochastic Frontier Analysis*. Cambridge University Press.
- Li, Tong, and Robert Rosenman.** 2001. "Cost Inefficiency in Washington Hospitals: A Stochastic Frontier Approach Using Panel Data." *Health Care Management Science*, 4: 73–81.
- Maruyama, Shiko.** 2011. "Socially Optimal Subsidies for Entry: The Case of Medicare Payments to HMOs." *International Economic Review*, 52(1): 105–129.
- Mazzeo, Michael J.** 2002. "Product Choice and Oligopoly Market Structure." *The RAND Journal of Economics*, 33(2): pp. 221–242.
- McGuire, Thomas G., Joseph P. Newhouse, and Anna D. Sinaiko.** 2011. "An Economic History of Medicare Part C." *Milbank Quarterly*, 89(2): 289–332.



- McKay, Niccie L., and Mary E. Deily.** 2005. "Comparing High- and Low-Performing Hospitals Using Risk-Adjusted Excess Mortality and Cost Inefficiency." *Health Care Management Review*, 30(4).
- McKay, Niccie L., Deily Mary E., and Fred H. Dorner.** 2002. "Ownership and Changes in Hospital Inefficiency, 1986-1991." *Inquiry*, 39(4): 388-399.
- Mello, Michelle M., Sally C. Stearns, and Edward C. Norton.** 2002. "Do Medicare HMOs still reduce health services use after controlling for selection bias?" *Health Economics*, 11(4): 323-340.
- Newhouse, Joseph P.** 1970. "Toward a Theory of Nonprofit Institutions: An Economic Model of a Hospital." *The American Economic Review*, 60(1): pp. 64-74.
- Ozcan, Yasar A., Luke Roice D., and Cengiz Haksever.** 1992. "Ownership and Organizational Performance: A Comparison of Technical Efficiency across Hospital Types." *Medical Care*, 30(9): 781-794.
- Pauly, Mark, and Michael Redisch.** 1973. "The Not-For-Profit Hospital as a Physicians' Cooperative." *The American Economic Review*, 63(1): pp. 87-99.
- Rosko, Michael D.** 1999. "Impact of Internal and External Environmental Pressures on Hospital Inefficiency." *Health Care Management Science*, 2(2): 63-74.
- Rosko, Michael D., and Ryan L. Mutter.** 2008. "Stochastic Frontier Analysis of Hospital Inefficiency." *Medical Care Research and Review*, 65(2): 131-166.
- Rosko, Michael D., and Ryan L. Mutter.** 2010. "Inefficiency Differences between Critical Access Hospitals and Prospectively Paid Rural Hospitals." *Journal of Health Politics, Policy and Law*, 35(1): 95-126.

- Seim, Katja.** 2006. “An Empirical Model of Firm Entry with Endogenous Product-Type Choices.” *The RAND Journal of Economics*, 37(3): pp. 619–640.
- Seitz, Shannon.** 2009. “Accounting for Racial Differences in Marriage and Employment.” *Journal of Labor Economics*, 27(3): pp. 385–437.
- Sloan, Frank A.** 2000. “Chapter 21 Not-for-profit ownership and hospital behavior.” In . Vol. 1, Part B of *Handbook of Health Economics*, , ed. Anthony J. Culyer and Joseph P. Newhouse, 1141 – 1174. Elsevier.
- Small, Kenneth A., and Harvey S. Rosen.** 1981. “Applied Welfare Economics with Discrete Choice Models.” *Econometrica*, 49(1): pp. 105–130.
- Starr, Paul.** 1982. *The Social Transformation of American Medicine*. Basic Books.
- Stephen Zuckerman, Jack Hadley, Lisa Iezzoni.** 1994. “Measuring Hospital Efficiency with Frontier Cost Functions.” *Journal of Health Economics*, 13(3): 255–280.
- Town, Robert, and Su Liu.** 2003. “The Welfare Impact of Medicare HMOs.” *The RAND Journal of Economics*, 34(4): pp. 719–736.
- Vitaliano, Donald F., and Mark Toren.** 1996. “Hospital Cost and Efficiency in a Regime of Stringent Regulation.” *Eastern Economic Journal*, 22(2): 161–175.

## APPENDIX A

### TABLES

Table A.1: Summary Statistics

	non-profit	for-profit	public
total costs (\$M)	74.07	19.98	20.81
total admissions	15,845	10,958	3,488
costs/admission	5,260	2,913	6,410
beds	86	90	27
competing hospitals	2	5	1
CMI	1.357	1.346	1.213
population density	226	426	46
% teaching	29.5	8.1	13.1
% system	69.9	90.6	40.8
proportion of hospitals	50.08	27.40	22.52
proportion of beds	45.95	41.66	12.39

Table A.2: Summary Statistics - by Market Size

	small	medium	large
total costs (\$M)	15.8	54.5	103.5
total admissions	2,424	14,648	29,949
costs/admission	7,394	4,338	3,919
beds	25	83	136
competing hospitals	0	2	12
CMI	1	1	1
population density	27	196	1,519
% teaching	0.028	0.162	0.407
proportion of hospitals	33.30	33.41	33.30
proportion of beds	8.66	26.33	65.01

Table A.3: Costs per Admission Matrix

	small	medium	large
non-profit	\$ 7,918	\$ 4,966	\$ 4,345
for-profit	\$ 3,913	\$ 2,656	\$ 2,586
public	\$ 8,318	\$ 4,684	\$ 4,678

Table A.4: Multinomial Logit Coefficients

	Group 2	Group 3
referral	-0.452** (0.149)	-3.408*** (0.314)
transplant	1.484* (0.740)	2.488*** (0.735)
teach	1.084*** (0.167)	2.257*** (0.165)
critical access	-2.199*** (0.103)	-5.239*** (0.414)
all inclusive	0.529 (0.330)	1.223*** (0.319)
new	1.449** (0.441)	1.766*** (0.440)
rehabilitation	0.863*** (0.120)	0.850*** (0.128)
long term	1.894*** (0.288)	2.408*** (0.286)
psych	0.194* (0.097)	0.282** (0.104)
cons	-9.357*** (2.041)	-5.209* (2.243)

Table A.5: Cost Function Estimates

	Raw	Treated
Admissions	-0.0979*** (0.0209)	-0.104*** (0.0165)
Outpatients	-0.177*** (0.0120)	-0.166*** (0.00928)
Price of Capital	0.341*** (0.0241)	0.343*** (0.0252)
Admissions <sup>2</sup>	0.0308*** (0.00179)	0.0314*** (0.00154)
Outpatients <sup>2</sup>	0.0265*** (0.00135)	0.0258*** (0.00114)
Price of Capital <sup>2</sup>	0.0230*** (0.00116)	0.0225*** (0.00116)
Admissions*Outpatients	-0.00869*** (0.00172)	-0.00863*** (0.00176)
Admissions*PriceofCapital	-0.00292 (0.00355)	-0.00386 (0.00363)
Outpatients*PriceofCapital	0.00333 (0.00184)	0.00323 (0.00184)
CMI	0.397*** (0.0172)	0.408*** (0.0136)
System Dummy	-0.00956 (0.0155)	-0.00479 (0.0147)
Teaching Dummy	0.207*** (0.0193)	0.292*** (0.0128)
Missing Dummy (Labor Price)	-0.0841*** (0.0191)	-0.0893*** (0.0143)
Missing Dummy (CMI)	-0.0123 (0.0217)	0.00352 (0.0211)
Constant	4.557*** (0.0298)	4.518*** (0.0219)
log-likelihood	-2444	-2412
N	5316	5316

Table A.6: Elasticities at Select Points

	mean	25%ile	median	75%ile
admissions	0.0339	0.0251	0.0310	0.0355
outpatients	0.0281	0.0202	0.0248	0.0291
price of capital	0.0164	0.0077	0.0128	0.0175

Table A.7: Cost Function Efficiency Estimates

Coeff	Raw	Treated
HHI	0.0750** (0.0283)	0.0538** (0.0207)
age	-0.00635*** (0.00136)	-0.00647*** (0.00160)
income	1.38e-7 (6.03e-7)	7.20e-7 (6.38e-7)
% white	0.00175*** (0.000319)	0.00183*** (0.000316)
prof	-0.219*** (0.0324)	-0.340*** (0.00653)
pub	-0.0840*** (0.0198)	-0.0600* (0.0287)
prof2	-0.0203 (0.0400)	0.128 (0.0873)
pub2	-0.0291 (0.0378)	-0.0465 (0.0757)
prof3	0.0723 (0.0403)	0.226** (0.0851)
pub3	-0.00330 (0.0414)	-0.0885** (0.0322)
popgrp2	-0.00125 (0.0243)	0.0533 (0.0504)
popgrp3	-0.0438 (0.0334)	-0.294*** (0.0464)
constant	0.341*** (0.0320)	0.371* (0.172)

Table A.8: Relative Efficiency Estimates

	raw			treated		
	small	medium	large	small	medium	large
For Profit	-.219*** (.0324)	-.239*** (.0239)	-.146*** (.0249)	-.340*** (.00653)	-.212** (.046)	-.113 (.137)
Public	-.084*** (.0198)	-.113*** (.0265)	-.0873** (.0367)	-.06** (.0287)	.107* (.0588)	-.149*** (.0105)

Table A.9: Comparison of Summary Statistics for Cawley, Chernew and McLaughlin (2005)

Variable	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max
Number of HMOs Active in Medicare+Choice	27,666	0.44	1.09	0	10	3109	4.877131	3.310948	0	17
CMS payment (Per enrollee, per month)	27,666	391.44	88.85	168.15	881.35	3108	712.7514	69.91314	662.32	1367.41
Average Medicare Part A Costs	27,666	2,213.62	488.78	385.18	5,658.37	3108	4108.918	819.9329	954.8039	8828.268
Average Medicare Part B Costs	27,666	1,219.05	257.87	482.03	2,910.01	3108	3515.541	599.8412	1857.2	11909.18
Number of General Practitioner Medical Doctors	25,830	23.24	77.02	1	2,605	3108	28.57079	87.46201	0	2605
Number of Registered Nurses	27,324	617.35	2,004.18	1	52,780	3108	556.945	2063.832	0	49795
Number of Hospitals	22,617	2.6	5.23	1	148	3108	1.991956	4.194146	0	111
Number of HMOs Active in Commercial Market	71,161	1.8	1.39	1	11					
Per Capita Income	27,657	16,792.50	3,781.89	6,306	52,277	3108	30337.54	8119.889	8579	132728
Poverty Rate Among Elderly	27,603	0.17	0.083	0.01	0.58	3108	0.100793	0.040683	0.016253	0.372026
Median Rent	27,666	319.97	94.75	140	926	3108	440.7014	122.1515	206	1185
% Adults High School Graduates	27,666	69.54	10.34	31.6	95.5	3108	77.33536	8.72752	34.7	97
% Adults College Graduates	27,666	13.42	6.47	3.7	53.4	3108	16.50795	7.80015	4.9	63.7
Number of Medicare Beneficiaries	27,666	10,835.20	31,799.90	14	877581	3108	11496.53	32386.8	16	946076
% Growth in Medicare Beneficiaries	27,666	0.31	0.23	-0.31	2.98	3108	1.61511	2.345646	-12.8983	31.7316
Medicare Beneficiaries in Neighboring Counties	27,291	58,662.80	89,838.50	994	1,452,320	3108	64588.81	103954.2	760	1753293
% Growth of Medicare Beneficiaries in Neighboring Counties	27,291	0.327	0.17	-0.10	1.38	3108	1.767726	1.42425	-3.91215	11.80743
% Population Urban	20,691	48.28	23.81	0.1	100	3108	40.13652	30.92595	0	100
Population Density	27,666	208.53	1,439.40	0.2	53,801.10	3108	244.5411	1675.87	0.1	66940.1
% Workers in Manufacturing	27,639	18.58	10.54	0.4	53.6					
% Workers White Collar	27,666	45.37	9.3	17.8	81.4	3108	35.36688	9.062371	13.58	76.05
Indicator: at Least One HMO Active in M+C	27,666	0.21	0.41	0	1					
Market Penetration of HMOs into Medicare	15,369	0.05	0.09	0	0.58					



Table A.10: Firm Pool Statistics

		mean	median	sd	min	max
Active Plans	All	4.479286	4	2.946508	0	15
	Non-Profit	0.727852	0	1.181569	0	9
	For Profit	3.751434	3	2.60392	0	13
Added Plans	All	6.16826	6	3.140994	0	26
	Non-Profit	2.003505	2	1.25298	0	13
	For Profit	4.164755	4	2.612946	0	18
	Adjacent Counties	4.984704	5	3.206885	0	25
	Top Firms	2.556087	2	1.37636	0	7

Table A.11: Average Part C Payment by number of active plans

active plans	markets	Average Payment
0	3	745.80
1	311	693.62
2	401	697.28
3	388	701.13
4	403	705.27
5	335	710.61
6	302	711.12
7	289	735.29
8	165	727.19
9	140	729.03
10	95	757.87
11	50	744.04
12	19	767.74
13	19	801.94
14	7	761.96
15	2	896.56

Table A.12: Subsidiary Overlap for Parent Organizations

Parent Company	Overlap with siblings	Overlap with outside firms	Ratio Siblings/Strangers
independent health association, inc.	3.33	0.14	23.16
blue cross of idaho health services, inc.	4.22	0.18	23.1
health alliance plan (hap)	4	0.17	22.96
blue cross and blue shield of massachusetts, inc.	5.5	0.24	22.58
aveta, llc.	42.5	2.04	20.85
presbyterian healthcare services	4	0.21	18.83
medica holding company	18.5	1.13	16.33
blue cross and blue shield of north carolina	5.5	0.34	16.05
university of pittsburgh medical center	4	0.35	11.57
blue cross and blue shield of minnesota	7	0.76	9.22
emblemhealth, inc.	4.5	0.75	6.01
mvp health care, inc.	1.78	0.32	5.52
highmark inc.	4.22	0.77	5.5
health net, inc.	4.44	1.08	4.12
blue cross blue shield of michigan	15	3.86	3.89
universal health care group, inc.	13	4.07	3.2
providence health & services	0.67	0.23	2.87
wellpoint, inc.	1.39	0.75	1.84
coventry health care inc.	1.07	0.63	1.71
aetna inc.	2.48	1.75	1.42
munich american holding corporation	8	5.65	1.42
america's 1st choice holdings of florida, llc	0.5	0.37	1.35
kaiser foundation health plan, inc.	1.39	1.13	1.23
blue cross and blue shield of florida	0.25	0.2	1.23
unitedhealth group, inc.	1.08	0.93	1.16
humana inc.	2.87	2.59	1.11
wellcare health plans, inc.	0.5	0.53	0.94
arcadian management services inc.	0.38	0.44	0.84
medical card system, inc.	1	1.2	0.84
healthspring, inc.	0.2	0.28	0.7
scan health plan	0.22	0.35	0.64
universal american corp.	1.28	3.78	0.34

Table A.13: Estimation Coefficients

---

Medicare Advantage Payment	5.759*** (0.4004)
Parts A+B Reimbursement	-0.247*** (0.01353)
Medicare Enrollees	0.488*** (0.0759)
Change in Enrollees	-0.452*** (0.00564)
number of hospitals	0.666*** (0.02222)
average income	-0.0271*** (0.00177)
population density	-0.00388*** ( $<0.001$ ) <sup>1</sup>
non-profit	-0.390*** ( $<0.001$ )
non-profit*payment	0.0556*** ( $<0.001$ )
distance to headquarters	-0.235*** ( $<0.001$ )
error	0.998*** (0.00173)
competition	-0.826*** (0.02015)
criterion function	026.3573

---

Table A.14: Raw Summary Statistics for MCBS Access to Care module

	Overall	Medicare	Medigap	Medicare Advantage
Age	71.8	65.9	74.9	75.8
Income	19,766	13,217	24,506	20,574
Health	2.803	3.185	2.63	2.634
White	78.8%	66.5%	87.8%	73.4%
Black	9.5%	15.9%	5.1%	9.4%
Hispanic	7.6%	11.0%	3.9%	13.8%
Married	47.2%	29.0%	58.9%	49.4%
Veteran	23.9%	17.8%	28.1%	23.7%
Female	55.7%	53.9%	56.1%	59.0%
High School	69.4%	54.6%	79.0%	69.7%
College	25.0%	15.1%	31.7%	23.6%
Total	15769	35.20%	52.10%	12.70%

Table A.15: Estimation Results

Variable	Estimate	
cost	0.000255*** (1.31e-08)	
network	-0.000426*** (0.000000197)	
	Medigap	Medicare Advantage
income	0.0894*** (0.000000857)	0.0592*** (0.00000113)
age	0.0516*** (0.00000645)	0.182*** (0.0000105)
age <sup>2</sup>	0.0000592*** (4.66e-08)	-0.000871*** (7.38e-08)
married	0.213*** (0.0000188)	0.214*** (0.0000244)
job	-0.356*** (0.0000265)	-0.0726*** (0.0000356)
veteran	0.464*** (0.0000215)	0.485*** (0.0000286)
health	-0.0935*** (0.00000632)	-0.116*** (0.00000838)
constant	-5.005*** (0.000231)	-10.57*** (0.000380)

Table A.16: Welfare Enhancement from Medicare Advantage

choice	mean	median	max	min
Medicare	\$474	\$565	\$1,631	\$6
Medigap	\$654	\$681	\$1,386	\$1
Medicare Advantage	\$675	\$715	\$1,542	\$8
Total	\$597	\$660	\$1,631	\$1

## APPENDIX B

### FIGURES

Figure B.1: Ownership Types and Population Density

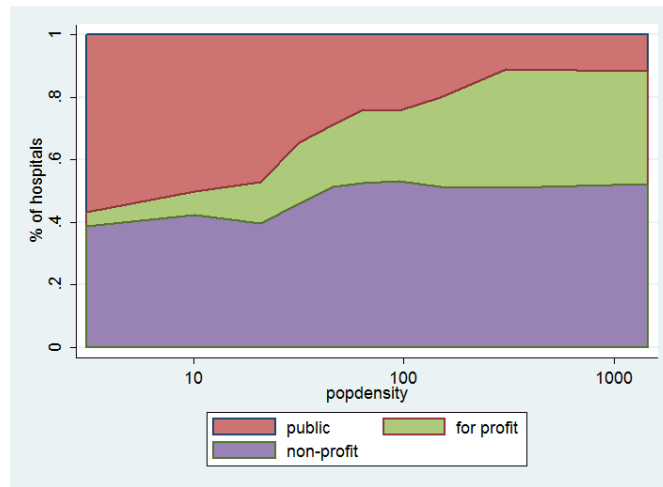


Figure B.2: Per Patient Costs and Population Density

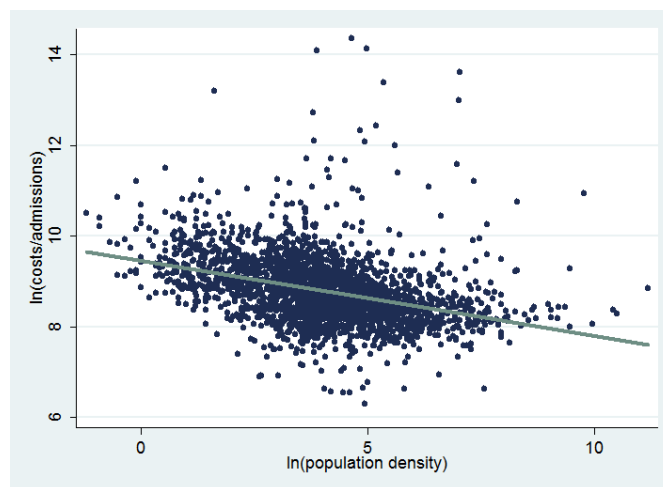


Figure B.3: Per Patient Costs and Market Type

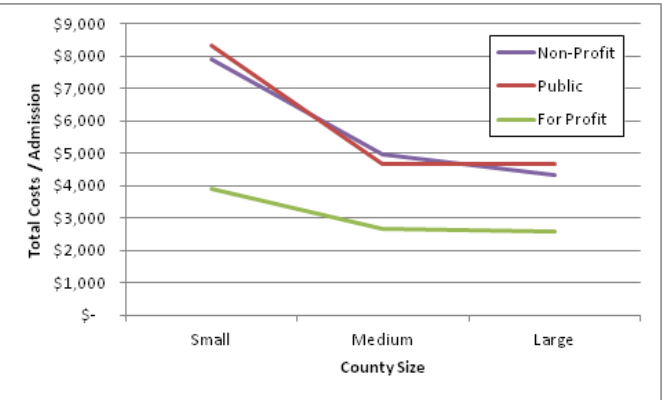


Figure B.4: Sample Hospital Locations

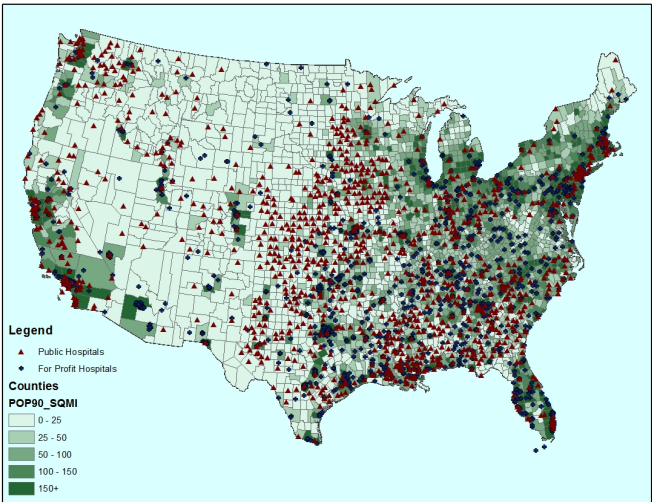




Figure B.5: Regions used for Multinomial Logit Analysis

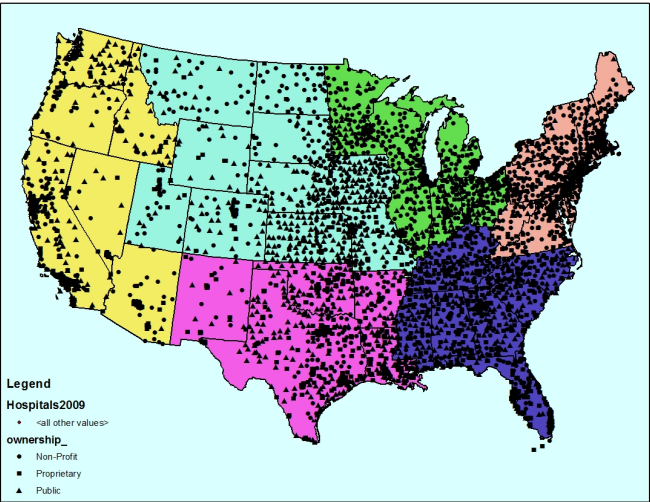


Figure B.6: Multinomial Results

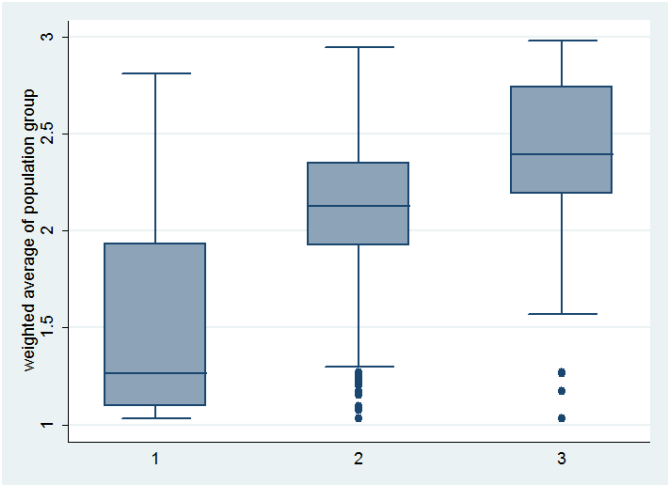


Figure B.7: Marginal Inefficiency of Ownership Types by Market Type

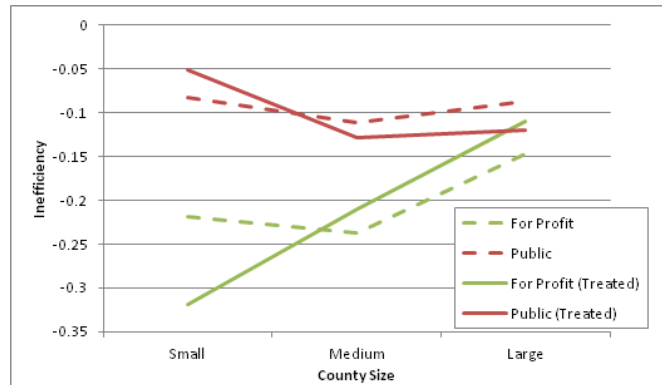


Figure B.8: Treated Hospital efficiency estimates by ownership and location

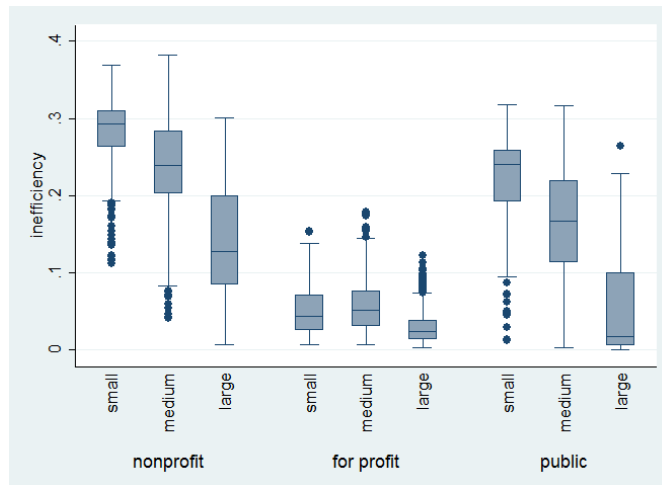


Figure B.9: Raw and Treated Hospital efficiency estimates by ownership and location

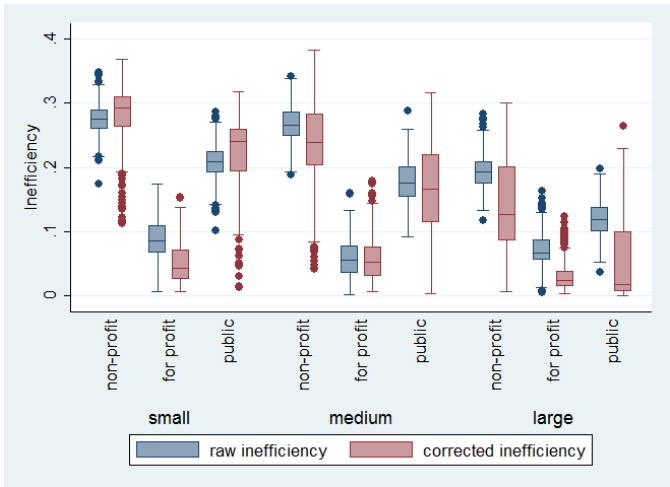


Figure B.10: For-Profit and Public Hospital Inefficiency in Small Markets

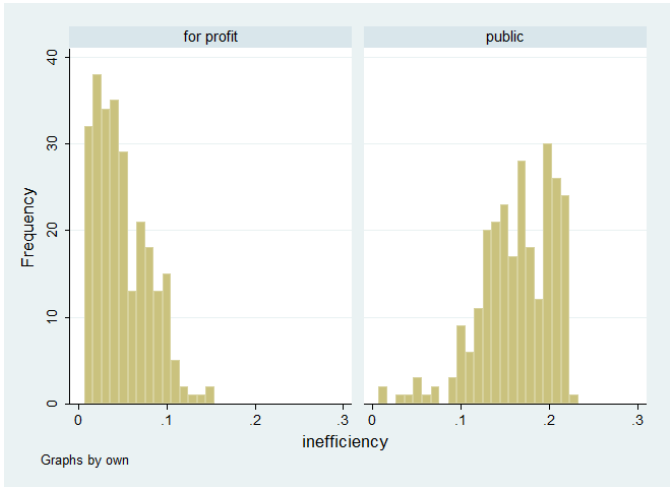


Figure B.11: Distribution of Active and Non-Active Plans

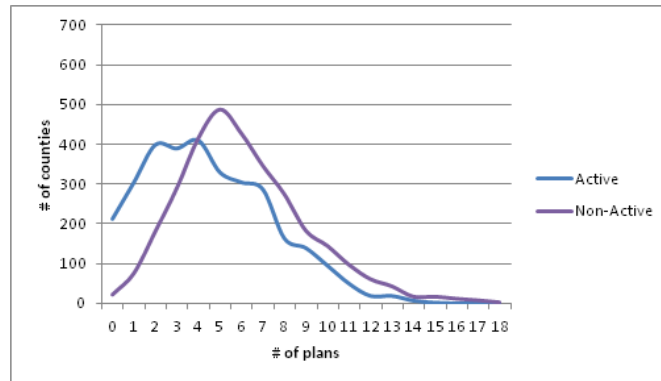


Figure B.12: Number of Active Firms in each County

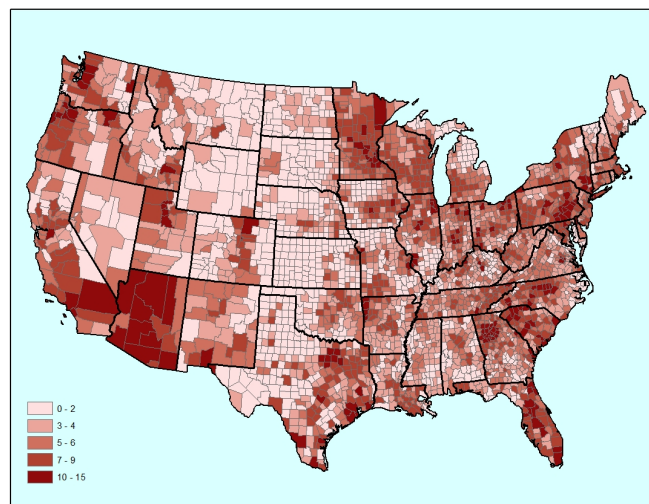


Figure B.13: Number of non-Active Plans in each County

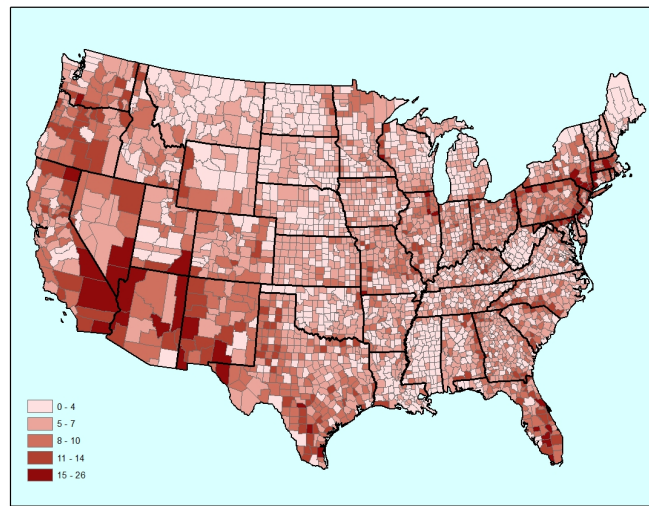


Figure B.14: % of Firms that are Non-Profit by County

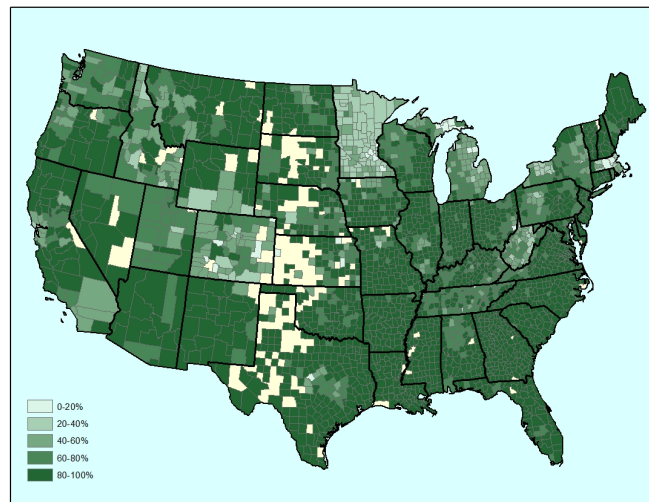


Figure B.15: Relationship of Base Payments and Number of Plans

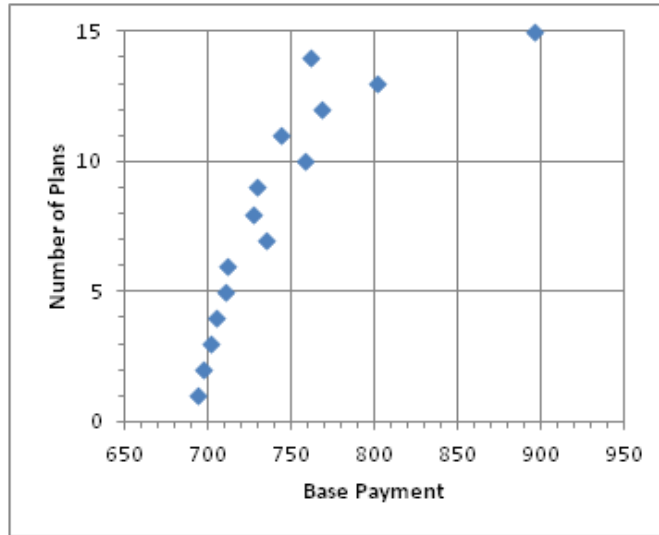


Figure B.16: Relationship of Base Payments and Ownership Composition

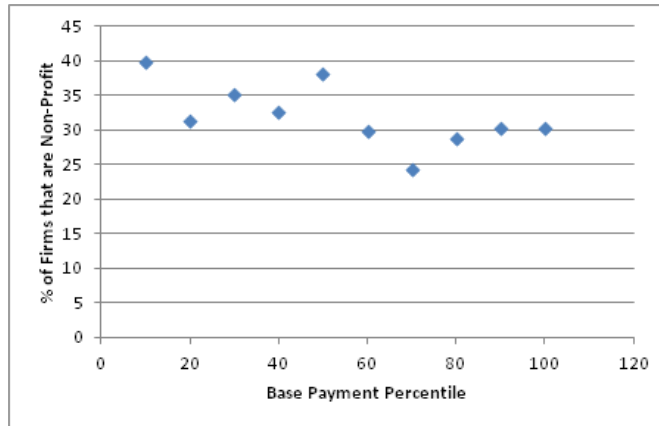


Figure B.17: Actual vs. Predicted Number of Participants in each Market

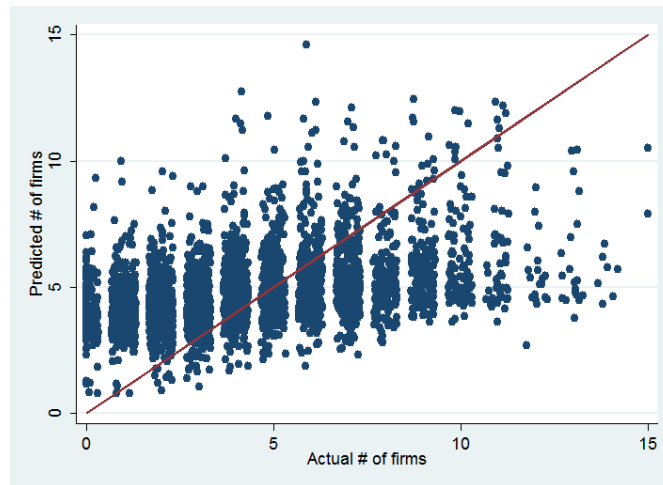


Figure B.18: Actual vs. Predicted Number of For Profits in each Market

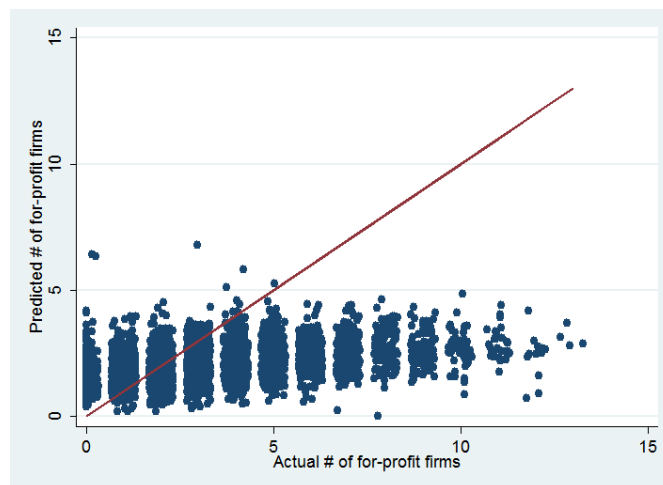


Figure B.19: % of Beneficiaries enrolled in Medigap Plans (by Plan Letter)

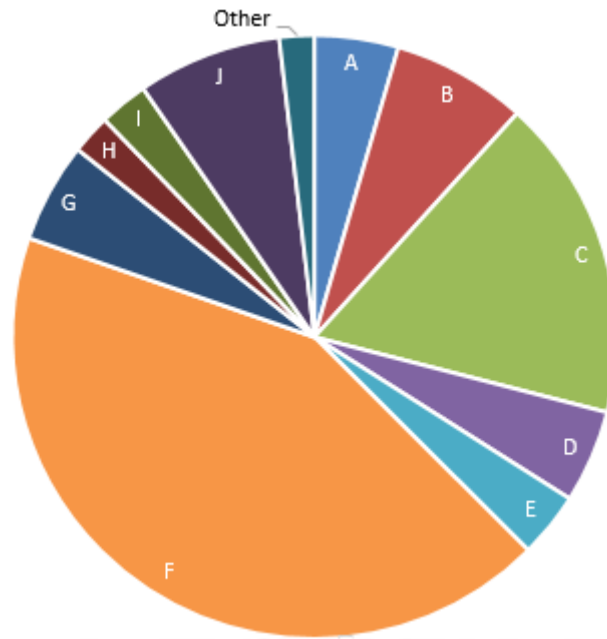


Figure B.20: % of Beneficiaries enrolled in N Medigap Plans

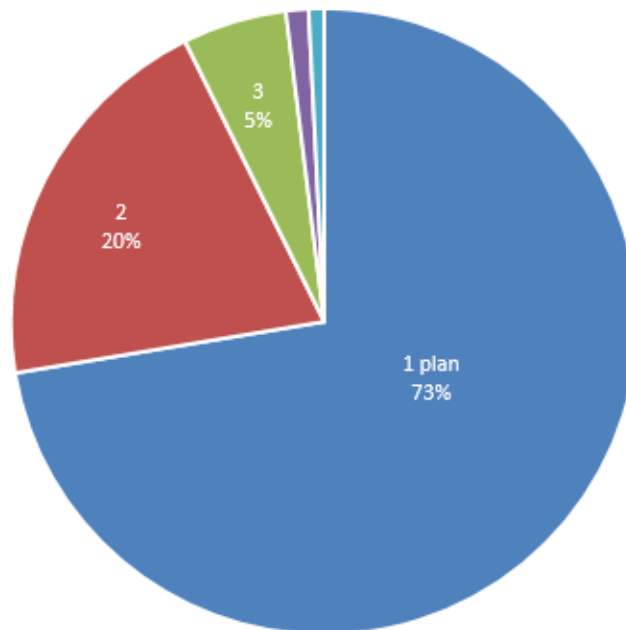




Figure B.21: Premiums paid by beneficiaries who have directly enrolled in a Medigap Plan (by Plan Letter)

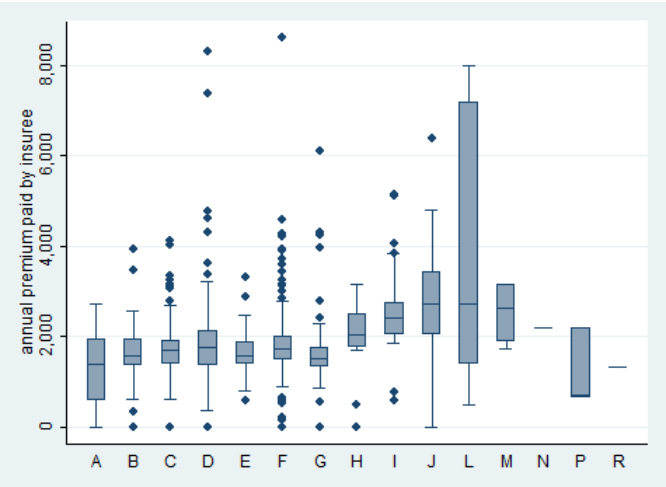


Figure B.22: Number of plans available to beneficiary

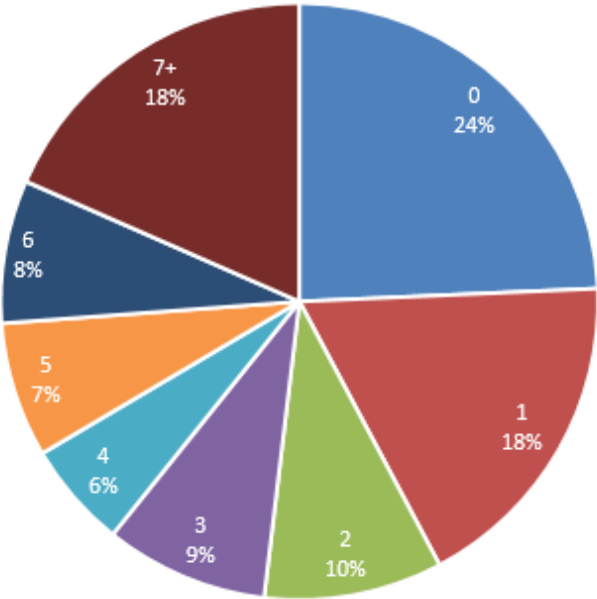


Figure B.23: Price of Medicare Advantage plans (with a non-zero premium)

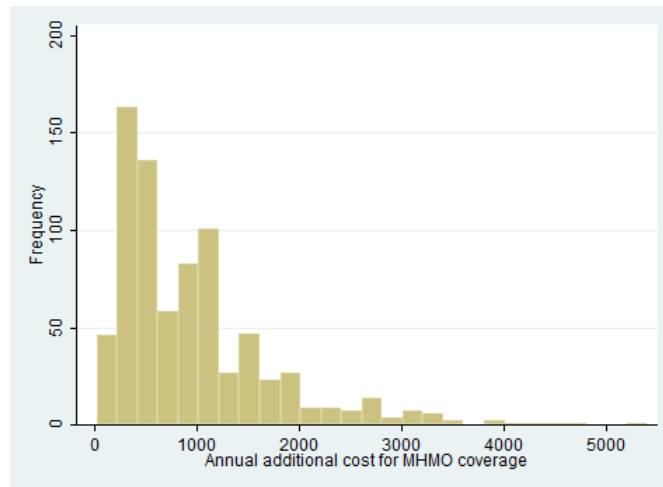


Figure B.24: Penetration of Medicare Advantage from December 2004-December 2005

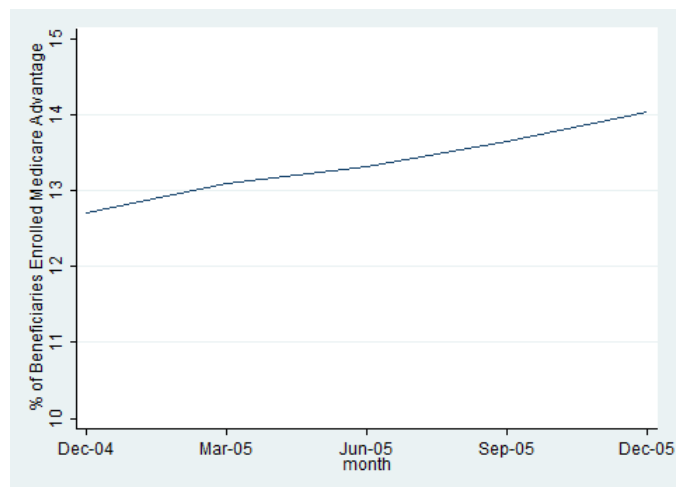


Figure B.25: Distribution of Risk Ratios by county

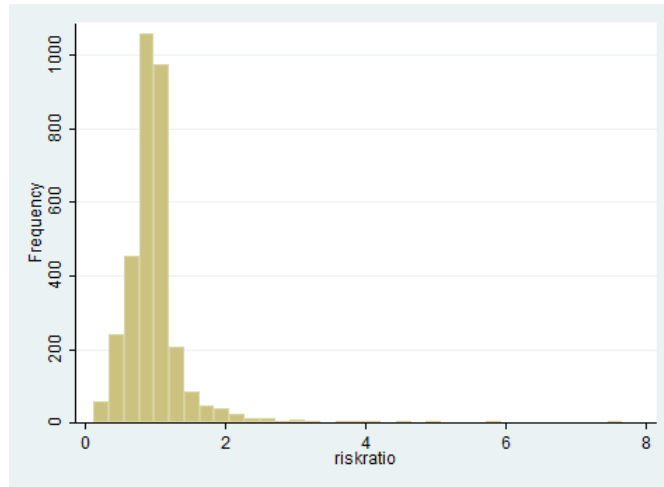


Figure B.26: Change in Consumer Surplus

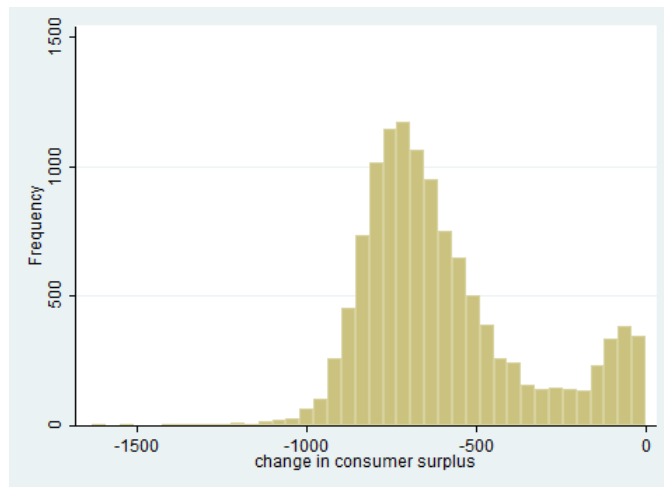


Figure B.27: Net Cost of Medicare Advantage (% increase relative to traditional Medicare)

